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Social Influence On Consumers' Online Review Behavior

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SOCIAL INFLUENCE ON CONSUMERS' ONLINE REVIEW BEHAVIOR

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DEDICATION

This dissertation is dedicated to my parents with gratitude for their unwavering love and support.

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After two years of intensive work on my doctoral dissertation, today is the day I write these acknowledgements. This process has been a valuable learning experience for me in hospitality and tourism management. I would like to thank several people who have given me generous help and support throughout this period. First and foremost, I would like to thank my dissertation committee chair and my advisor, Dr. Fang Meng, for her valuable suggestions and academic support during the completion of my dissertation. She has always been willing to help me, and my doctorate would have not been possible without her guidance, encouragement, and inspiration. She is my role model for a great researcher. Similarly, I wish to thank my dissertation committee members, Dr. Hudson, Dr. Jeong, Dr. Pan, and Dr. Janakiraman, for their insightful comments and suggestions to refine my dissertation. I would also like to thank them for their extensive professional guidance and support. Last but not least, I would also like to thank my parents and my older sister for their endless support and unconditional love.

ABSTRACT

Online reviews constitute an important source of word-of-mouth, which can affect consumers' product choices as well as company sales and profitability. Therefore, understanding the factors underlying consumers' online posting behavior is essential for business success and relevant knowledge development. This dissertation consists of three independent but closely related studies focusing on hotel and restaurant contexts. The objectives of this dissertation are to investigate how prior reviews and disconfirmation (i.e., the deviance between post-consumption evaluations and other consumers' prior average review rating) may affect subsequent consumers' online review-posting behavior in terms of their willingness to post online reviews, the review ratings they ultimately choose, and the content characteristics of their reviews.

Utilizing an experimental design method, Study 1 examines the influence of disconfirmation on consumers' willingness to post online reviews and on their ultimate review rating decisions. The findings of this study suggest that disconfirmation can increase consumers' willingness to post online reviews, and positive disconfirmation can increase consumers' online review ratings. Compared with substantial variance in prior review ratings, disconfirmation effects are stronger when the variance of prior ratings is smaller. Using an econometric and text mining method based on online review data from Yelp, Study 2 investigates the influence of disconfirmation on the content characteristics of consumer-generated online reviews. The findings of this study reveal that

disconfirmation compels consumers to write longer and sentimental reviews and to explain why they have deviated from past consumers. Negativity bias was also found to exist in disconfirmation effects, such that negative disconfirmation shows stronger effects than positive disconfirmation. Again using online review data from Yelp, Study 3 explores the impact of prior average review ratings on subsequent consumers' post-consumption review ratings as well as the factors contributing to customers' conformity or differentiation behavior. The findings of this study imply that prior average review rating exerts a positive influence on subsequent review ratings for the same restaurant, but the effect is attenuated by variance in existing review ratings. Moreover, social influence is stronger for consumers who had a moderate dining experience or invested less cognitive effort in writing online reviews. Compared with reviewers classified by Yelp as "elite," non-elite reviewers appear more susceptible to the social influence of prior average review rating.

This dissertation contributes to the hospitality marketing literature and general marketing literature by providing new theoretical insights. Moreover, the empirical findings of this dissertation also unveil important managerial implications regarding online review management and digital marketing strategies for hospitality firms and online review communities.

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CHAPTER 1

GENERAL INTRODUCTION

1.1 Research Background

With the advent of the internet and social media, online reviews have become increasingly popular as an important source of word-of-mouth (WOM), which can influence product sales and profitability (Chevalier & Mayzlin, 2006; Ye, Law, & Gu, 2009; Zhu & Zhang, 2010). Therefore, understanding the factors behind consumers' online review-posting behavior is essential for business success and theoretical development. Despite growing scholarly interest in this research topic, existing literature has provided a limited understanding of individuals' decisions to provide product reviews and the features that contribute to those decisions (Moe & Schweidel, 2012).

Consumers often peruse product reviews online prior to making purchases. They may also be exposed to reviews written by past customers on a product review page after purchasing (i.e., when they return to a site to post their own online reviews). Scholars commonly assume that prior reviews will influence an individual's online review behavior only after product purchase and consumption. For example, Moe and Schweidel (2012) and Schlosser (2005) each reported that consumers tend to observe prior consumers' opinions when making rating decisions and then modify their own evaluations accordingly. But the influence of prior reviews may also apply when an individual browses online reviews prior to purchase, which can shape pre-purchase expectations of a product. Consumers also form post-consumption evaluations based on their product consumption experience and may encounter a certain level of expectation-evaluation disconfirmation at the same time. Thereby this dissertation investigates how prior reviews and disconfirmation (i.e., the discrepancy between post-consumption evaluations and prior average review rating posted by other consumers) may influence consumers' online review-posting behavior in terms of their willingness to post online reviews, their chosen review ratings, and the contents of their reviews.

1.2 Research Significance

Prior studies have contended that consumer-generated reviews are truthful and unbiased reflections of consumers' product and service experiences (Hu, Liu, & Sambamurthy, 2011). However, an emerging literature stream counters that consumers' online review behavior is influenced by review rating environments, including prior average review ratings and variance in prior ratings (Ho, Tan, & Wu, 2017; Lee, Hosanagar, & Tan, 2015; Li & Hitt, 2008; Moe & Schweidel, 2012). This implies that consumers' online review behavior may well be socially influenced. Essentially, consumers' product experiences and others' opinions of the same product may affect consumers' online review behavior, including their willingness to post online reviews, ultimate review rating decisions, and review content characteristics.

A comprehensive literature review has identified several research gaps related to this topic. First, previous literature offers limited understanding regarding the social influence process of consumers' online review behavior, especially the factors that may influence (i.e., strengthen or weaken) this process. The literature on experience-oriented hospitality products is especially scarce. Second, although previous studies have demonstrated that consumers' product experiences and other consumers' prior reviews could influence online review behavior, interaction effects have rarely been mentioned. In the meantime, an increasing number of companies have begun to manipulate online reviews in various ways (e.g., by posting deceptive positive reviews for their own products, posting deceptive negative reviews for their competitors' products, or both; Anderson & Simester, 2014; Hu, Bose, Koh, & Liu, 2012). Therefore, it is important to test the disconfirmation effects for experience-oriented hospitality products.

1.3 Research Framework

This dissertation includes three related studies. These studies focus on hotel and restaurant settings rather than manufactured goods, as hotel and restaurant products are more experience-oriented and possess characteristics of intangibility, variability, perishability, and inseparability. Therefore, online reviews for hotels and restaurants are more likely to be socially influenced than those for manufactured products.

Using an experimental design method, Study 1 explores the influence of disconfirmation (i.e., the deviance between post-consumption evaluations and prior average review ratings of the same product) on consumers' post-consumption willingness to post online reviews and accompanying review ratings. This study examines the following research questions: (1) How does disconfirmation influence consumers' willingness to post online reviews? (2) How does disconfirmation influence consumers' review rating decisions? (3) What is the underlying motivation of consumers' online review posting behavior when they encounter disconfirmation? and (4) How does the variance in prior review ratings moderate the influence of disconfirmation on consumers' willingness to post online reviews and their ultimate review ratings? By applying econometric and text mining methods to online secondary data, Study 2 examines the influence of disconfirmation on the content characteristics of consumer-generated online reviews. This study investigates the following two research questions: (1) How does disconfirmation affect online review content characteristics, including review sentiment, review length, and review content reflecting causal-explanation? (2) Are the influences of positive disconfirmation and negative disconfirmation symmetrical? Moreover, using an econometric method based on online secondary data, Study 3 examines the impact of prior average review rating on subsequent consumers' post-consumption review ratings as well as the moderation effects of consumers' experience extremity, cognitive effort, review-writing expertise, and variance of prior review ratings.

This dissertation is grounded in several fundamental theories:

Social influence theory. Individuals may experience conformity needs (Sherif, 1936), uniqueness needs (Fromkin, 1970), and normative conflict (Packer, 2008) in a social group, with the most salient feature depending on situational factors. People conform to the peers they know as well those they do not (Darley & Latane, 1968); the uniqueness motivation is activated when people feel too similar to other group members (Snyder & Fromkin, 1980). However, when people perceive a substantial discrepancy from the group norm and believe the group's opinion to be harmful, they may exhibit a strong tendency toward normative conflict (Hornsey, Oppes, & Svensson, 2002) to the neglect of pressure to conform. This dissertation examines the influence of prior average review rating on subsequent consumers' online review behavior; therefore, social influence is applied as a core theory.

Expectancy-disconfirmation theory. Expectancy-disconfirmation theory, proposed by Oliver (1980), is a well recognized explanation for customer satisfaction. The determination of customer satisfaction/dissatisfaction is reached through a comparison between customer expectations and perceived performance (Oliver, 1980; Woodruff, Cadotte, & Jenkins, 1983). If performance is lower than expectations, consumers experience negative disconfirmation; if performance is higher than expectations, they experience positive disconfirmation. This dissertation examines the influence of disconfirmation between post- consumption evaluations and prior average review ratings on consumers' online review-posting behavior in terms of their willingness to post reviews, ultimate rating decisions, and the content characteristics of what they write. Given the emphasis of this theory on customer satisfaction, expectancy-disconfirmation theory is heavily incorporated into this dissertation.

Prospect theory. According to prospect theory (Herr, Kardes, & Kim, 1991; Kahneman & Tversky, 1979), people are highly loss-averse and show strong negativity bias. Anderson and Sullivan (1993) noted that consumers tend to focus more on negative disconfirmation compared to positive disconfirmation and proposed an asymmetrical loss function to explain the relationship between disconfirmation and customer satisfaction. This dissertation tests the asymmetrical effects of positive disconfirmation and negative disconfirmation on review content characteristics. Therefore, prospect theory is employed accordingly.

Elaboration likelihood model (ELM). ELM is an underlying theory of this dissertation for two reasons: (1) ELM examines two major influence processes, including the central and peripheral routes; and (2) ELM explains the distinct outcomes of the above two processes contingent on both message and individual characteristics (Bhattacherjee & Sanford, 2006). Consumers who critically deliberate over their product and service experiences are more likely to choose a central route, and review ratings posted by such consumers are less likely to be socially influenced by prior average review rating (Ma et al., 2013). In contrast, individuals who rely on positive or negative cues or others' opinions to make decisions, including those who consider their product and service experiences only superficially, are more likely to choose the peripheral deliberation route (Kim & Benbasat, 2003). Review ratings posted by consumers using peripheral routes are more likely to be socially influenced by prior average review ratings (Ma et al., 2013). This dissertation investigates factors (including reviewer and review characteristics) that could potentially influence the degree to which a consumer's review rating decision is socially influenced by prior average review rating.

CHAPTER 2

WHEN YOUR EXPERIENCE DEVIATES FROM OTHERS': EXPLORING THE IMPACT OF DISCONFIRMATION ON CONSUMERS' ONLINE REVIEW BEHAVIOR

2.1 Introduction

Consumers increasingly depend on digitized, online user-generated content, such as online reviews, when making purchase decisions (Hu, Bose, Gao, & Liu, 2011; Hu, Liu, & Sambamurthy, 2011; Muchnik, Aral, & Taylor, 2013), especially about experience-oriented tourism and hospitality products (Yoo & Gretzel, 2008). According to extant literature, the average review rating (Öğüt & Onur, 2012; Tsao et al., 2015; Vermeulen & Seegers, 2009; Ye, Law & Gu, 2009), number of online reviews (Chatterjee, 2001; Duan et al., 2008; Zhu & Zhang, 2010), and variance in online reviews (Sun, 2012; Xie, Zhang, & Zhang, 2014; Ye et al., 2009; Ye et al., 2011; Zhu & Zhang, 2010) can affect consumers' purchase intentions, online product sales, and firms' financial performance. Given the importance of such reviews, the factors influencing consumer online review behavior constitute an important and promising area of research.

Previous studies have shown that an individual's product experience and others' opinions can influence consumers' post-consumption willingness to post online reviews. For example, Anderson (1998) identified a U-shaped relationship between consumer satisfaction and word-of-mouth (WOM) in offline settings, such that consumers who are either highly satisfied or highly dissatisfied tend to engage in greater WOM than those who are moderately satisfied. Similarly, Dellarocas and Narayan (2006) reported that compared to consumers with moderate opinions, those with extremely positive or negative viewpoints are more likely to post online reviews for movies. Ho, Wu, and Tan (2017) indicated that the U-shaped relationship is asymmetrical, noting that consumers' review-posting propensity is affected to a larger extent by dissatisfaction than satisfaction. Moreover, an emerging literature stream has revealed that subsequent consumers' online review behavior is affected by environmental rating-related factors, such as the prior average review rating and the variance of prior ratings (Ho, Tan, & Wu, 2017; Lee, Hosanagar, & Tan, 2015; Li & Hitt, 2008; Moe & Schweidel, 2012; Schlosser, 2005). To reduce uncertainty and risk, consumers often peruse product reviews online prior to finalizing a purchase, and these reviews are likely to shape their expectations about the product or service (Ho, Wu, & Tan, 2017; Mauri & Minazzi, 2013). Moreover, consumers can see prior reviews on a review page after making a consumption but before posting their own reviews (Hong et al., 2016; Ma et al., 2013). In sum, prior reviews posted by other consumers will likely influence subsequent consumers' online review behavior before and after purchase. Although studies have demonstrated that a consumer's own product experience and existing reviews can influence his/her review behavior, the interaction effect between prior reviews and a consumer's own product evaluation has rarely been studied.

Adding to this complexity, companies have increasingly begun to strategically manipulate online consumer reviews so as to influence consumers' purchase decisions, either by posting deceptive positive reviews of their own products, fabricating negative reviews about their competitors, or both (Anderson & Simester, 2014; Dellarocas, 2006; Gormley 2013; Hu, Bose, Koh, & Liu, 2012; Ho, Wu, & Tan, 2017). Hu, Bose, Gao, and Liu (2011) reported that it is not uncommon for a company to engage in review manipulation by paying individuals to improve or otherwise modify online reviews. For example, in October 2015, the serviced apartments chain Meriton reportedly have paid consumers to change low and moderate ratings on the TripAdvisor website (Jabour, 2015). Moreover, some companies have collaborated with TripAdvisor to help hotels increase their rankings, such as through Revinate post-stay surveys (Murphy, 2014) and Review Direct produced by Market Metrix (Waite, 2013). Some restaurant owners even post positive online reviews for themselves, as a number of review websites do not require true customer identification, such as Yelp (Gössling, Hall, & Andersson, 2018).

Given the apparent prevalence of online review manipulation in the hospitality industry and the possible social influence of prior online reviews, consumers are highly likely to encounter a certain level of disconfirmation (i.e., discrepancy between their own post-consumption evaluations and prior review ratings of the same product), which may affect their online review behavior. This study therefore investigates how disconfirmation shapes consumer online review-posting behavior in terms of consumers' willingness to post online reviews and their ultimate review rating decisions. Specifically, this study examines the following research questions: (1) Does disconfirmation influence consumers' willingness to post online reviews? (2) Does disconfirmation influence consumers' review rating decisions? (3) What is the underlying motivation of consumers' online review-posting behavior when they encounter disconfirmation? and (4) How does variance in prior review ratings moderate the influence of disconfirmation on consumers' willingness to post online reviews and their ultimate review ratings? This study will contribute to the literature on social influence and online review-posting behavior, the relationship between disconfirmation and consumer post-consumption behavior, and research on the consequences of online review manipulation.

2.2 Literature Review and Research Hypotheses

2.2.1 Disconfirmation and Willingness to Post Online Reviews

According to social influence theory, individuals simultaneously experience conformity needs (Deutsch & Gerard, 1955; Sherif, 1936), uniqueness needs (Fromkin, 1970), and normative conflict (Packer, 2008) in a social group, with the dominating force contingent on situational characteristics. In terms of conformity needs, people tend to conform to social influence from peers with whom they are familiar as well as those they do not know (Darley & Latane, 1968). By conforming to others, people may make fewer mistakes, invest less mental effort in tasks, and avoid compromising their reputation (Cialdini, 2009).

The uniqueness motivation is activated when people feel as though they are too similar to other group members and thus take measures to reclaim their uniqueness and reduce negative affect induced by a lack of differentiation (Snyder & Fromkin, 1980). For instance, people who perceive themselves as too much like other group members are more apt to conform less during a judgment task and contribute less to the task overall (Duval, 1976). Applying this logic, the present author proposes that when a consumer's product experience is consistent with the majority of other consumers', he/she may sense excessive similarity and become increasingly motivated to make him- or herself distinct. Correspondingly, the consumer can attain the objective of remaining unique in the online review community by contributing less to the review task and choosing not to submit a product rating and review at all.

When people are certain in their judgments but perceive a large discrepancy from the group norm (and believe the group's opinion is harmful), they may exhibit strong normative conflict (Ashforth, Kreiner, & Fugate, 2000; Hornsey, Oppes, & Svensson, 2002). For example, Sridhar and Srinivasan (2012) reported that an online reviewer will experience normative conflict when product failure occurs and the personal product experience simultaneously deviates to an extreme degree from that of most other group members. In this case, consumers tend to overlook conformity pressure and instead behave altruistically even if their actions deviate from the majority (Hornsey, Oppes, & Svensson, 2002), especially if they believe their actions will benefit the group (Dreu, 2002; Louis, Taylor, & Neil, 2004). Packer (2008) pointed out that normative conflict induces greater dissenting behavior when people are given the opportunity to make their behaviors highly visible and to explain the reason behind their deviation. In the current study, when a consumer's product experience largely deviates from the majority, the consumer is expected to encounter a high degree of normative conflict. By providing a distinct online rating (compared to the majority) based on his/her own personal product experience, the consumer reduces normative conflict and has a motive to correct seemingly inaccurate online ratings provided by other consumers (Sridhar & Srinivasan, 2012). Hence, the following hypothesis is proposed:

Hypothesis 1 (H1): *Disconfirmation (vs. confirmation) leads to increased willingness to post online reviews.*

2.2.2 Disconfirmation and Online Review Ratings

Since Oliver's (1977, 1980) work, expectation-disconfirmation theory (EDT) has been widely used in the literature to explain customer satisfaction. Oliver (1980) introduced the expectancy-disconfirmation framework and described how judgments of satisfaction are reached under this theory. Specifically, consumers form expectations of certain products they intend to buy, after which their perceived quality of the product is generated from the consumption process. Disconfirmation occurs if their own quality evaluation deviates from their pre-purchase expectations. EDT suggests that customer expectations and perceived quality lead to post-purchase customer satisfaction through the mediation effect of disconfirmation. Expectation is the baseline, and disconfirmation serves as a major force that can either increase or decrease the level of customer satisfaction from the baseline. If positive disconfirmation occurs (i.e., the perceived product performance is better than the customer's expectations), consumers will be more satisfied with the product. In contrast, if negative disconfirmation takes place (i.e., the perceived product performance does not meet the customer's expectations), consumers will be dissatisfied. Yi (1989) conducted a comprehensive literature review on customer satisfaction and named expectations, perceived quality, and disconfirmation as the main antecedents of customer satisfaction. EDT has been applied to elucidate satisfaction in retail settings (Anderson & Sullivan, 1993) and IT use (Bhattacherjee, 2001). EDT has also been widely incorporated into the tourism and hospitality management literature. For example, Pizam and Milman (1993) found that a customer's satisfaction/dissatisfaction with a destination is well predicted by the disconfirmation between tourist expectations and the perceived outcome of the trip. Alan (2003) reported that the disconfirmation between the expected and actual level of food and service quality, rather than the absolute level, determines how well customers tip their servers. Disconfirmation can also affect consumers' post-purchase behaviors, such as repeat purchases and continued use of a product (Anderson & Sullivan, 1993; Bhattacherjee, 2001) along with post-purchase complaints (Bearden & Teel, 1983).

In a study published in *Science*, Muchnik, Aral, and Taylor (2013) designed a field experiment on a social news website and found prior news ratings to significantly influence subsequent rating behavior. Specifically, down-rated comments (i.e., those eliciting negative disconfirmation between prior reviewers' evaluations and the perceived quality of the focal reviewer) were likely to be down-rated, but this was offset by a larger correction effect (i.e., a higher probability of being up-voted). This correction effect neutralized the social influence of down-rated comments. Similarly, correction to biased online ratings was also likely when a consumer's perceived product quality disconfirmed the average rating of existing online reviews. Specifically, to correct biased, misleading, or inaccurate online review ratings, a consumer is likely to rate a product above his/her perceived product quality when encountering positive disconfirmation but below his/her perceived product quality when encountering negative disconfirmation. Accordingly, H2 is proposed:

Hypothesis 2 (H2): *Disconfirmation (vs. confirmation) has a significant impact on consumers' online review ratings.*

2.2.3 Moderating Effect of Prior Review Ratings' Variance

In the marketing literature, *expectation* is defined as "an anticipation of future consequences based on prior experience, current circumstances, or other sources of information" (Yi & La, 2003, p.23). Research in service marketing suggests that online reviews constitute an antecedent of customer expectations, with positive reviews increasing consumers' expectations and negative reviews decreasing them (Ho, Wu, & Tan, 2017; Mauri & Minazzi, 2013). For instance, Mauri and Minazzi (2013) found that before deciding to book a hotel, consumers usually check online reviews, which establish their expectations for that specific hotel. In a consumption context, expectation functions as a comparative referent when evaluating product performance and subsequent customer satisfaction (Yi & La, 2003).

Confidence is an important dimension of expectation (Yi & La, 2003), referring in this case to "a cognitive component that reflects the degree of conviction or certainty with which a belief or attitude is held" (Krishnan & Smith, 1998, p. 276). Consumers can hold the same expectation valence but may exhibit different levels of expectation confidence. Yi and La (2003) noted that expectation confidence can be measured by the probability or certainty of outcomes expected from a product purchase or consumption.

In the online review context, Yin, Mitra, and Zhang (2016) stated that a consumer's level of confidence in his/her initial opinion of a product (i.e., product expectations) can be measured by the dispersion (i.e., standard deviation) of other consumers' prior review ratings. Review rating dispersion reflects the consensus among prior consumers (Yin, Mitra, & Zhang, 2016), with a high degree of dispersion indicating low agreement among customers (Moe & Trusov, 2011). According to Petrocelli et al. (2007), lower agreement leads consumers to be less confident in the validity of average review ratings, which in turn leads to less certainty in their initial product expectations. In other words, consumers' disconfirmation tends to be less pronounced when expectations are uncertain.

Hart et al. (2009) indicated that as people become less confident in their expectations or initial beliefs, they tend to experience less psychological discomfort upon encountering disconfirmation. Spreng and Page (2001) also mentioned that higher expectation confidence renders expectancy-disconfirmation more useful and diagnostic for judgments. Several studies have indicated that confidence can moderate the attitude–behavior relationship (Bennett & Harrell, 1975; Fazio & Zanna, 1978; Krishnan & Smith, 1998). In a laboratory experiment, Spreng and Page (2001) found confidence in expectations to moderate the influence of disconfirmation on customer satisfaction, with higher confidence leading to a significant influence of disconfirmation on satisfaction and lower confidence leading to an insignificant influence. Similar findings were revealed in a family restaurant context: the influence of disconfirmation (between expectations and perceived performance) on satisfaction was stronger for customers holding greater expectation confidence than for those holding less (Yi & La, 2003). Consumers with high expectation confidence tend to judge expectancy-disconfirmation more accurately and thus treat disconfirmation as a prominent factor when evaluating satisfaction (Yi & La, 2003). These trends inform the following hypotheses.

Hypothesis 3a (H3a): *The variance of prior ratings moderates the direct influence of disconfirmation on consumers' willingness to post online reviews; the influence is stronger when the variance of prior ratings is smaller and weaker when the variance is larger*.

Hypothesis 3b (H3b): *The variance of prior ratings moderates the direct influence of disconfirmation on consumers' online review rating decisions; the influence is* *stronger when the variance of prior ratings is smaller and weaker when the variance is larger*.

2.2.4 Underlying Mechanism of Disconfirmation Effects

The mechanism of disconfirmation effects on consumers' willingness to post online reviews and review rating decisions is associated with extant studies on why consumers engage in post-purchase WOM. Engel, Blackwell, and Miniard (1993) named five motivations for traditional WOM behavior, namely concern for others, self-enhancement, involvement, dissonance reduction, and message intrigue. Despite the study's revelations, Engel, Blackwell, and Miniard's (1993) work was criticized for lacking a typology. Sundaram, Mitra, and Webster (1998) further proposed that motives for engaging in positive WOM are different from those related to negative WOM, classifying traditional WOM motivations into two categories: (1) motivations for positive WOM, including altruism, helping a company, self-enhancement, and product involvement; and (2) motivations for negative WOM, including altruism, vengeance, advice-seeking, and anxiety reduction.

Drawing on the above literature, Hennig-Thurau et al. (2004) extended previous studies to an online context and proposed eight motivations for spreading electronic WOM (eWOM), including venting negative feelings, platform assistance, concern for other consumers, extraversion/positive self-enhancement, helping the company, economic incentives, social benefits, and advice-seeking. Among these, concern for other consumers, social benefits, economic incentives, and expressing positive feelings were deemed the primary motivations behind eWOM (Hennig-Thurau et al., 2004). Similar findings have been reported in hospitality and tourism literature. Yoo and Gretzel (2008) conducted an online survey of a TripAdvisor traveler panel and identified seven motivations for writing online travel reviews. They noted that concern for other consumers, enjoyment, and helping the company were major motivations. Later, Bronner and de Hoog (2011) reported that the motivations of vacationers who contribute to online review sites are self-directed motivation, social benefits, consumer empowerment, and helping the company, the most frequently mentioned of which was concern for others. Although previous literature has comprehensively assessed eWOM motivations, consumers' motivations when encountering disconfirmation remain unknown.

Concern for other consumers, as a prime motivation for eWOM as revealed by previous literature, refers to "the desire to help other customers with their purchase decisions, to save others from negative experiences, or both" (Hennig-Thurau et al., 2004, p.42). For example, a consumer with concern for others might compose an online review simply to prevent others from purchasing a poor product. According to Hennig-Thurau et al. (2004), concern for other consumers is strongly associated with altruism, which has been acknowledged as an important motivation in other studies (Ho & Dempsey, 2010; Sundaram, Mitra, & Webster, 1998). This motivation can apply to positive and negative experiences (Hennig-Thurau et al., 2004). For products in the hospitality industry, such as a hotel or restaurant, concern for others is an essential motivation due to the intangibility of service-oriented products and the inseparability of production and consumption (Jeong & Jang, 2011; Yoo & Gretzel, 2008). Therefore, most customers rely on WOM or eWOM when making purchase decisions.

This motivation tends to become stronger when an individual's purchase/consumption experience is significantly higher or lower than the average rating of existing online reviews (i.e., positive or negative disconfirmation), leading to the sense that an online review rating may not be accurate and could even be misleading. In the case of positive disconfirmation, consumers are likely to demonstrate greater motivation to write online reviews to help others through their own positive experiences and to assist others in selecting the right product. For negative disconfirmation, customers tend to be more motivated to provide online product reviews to warn others of their own negative product experiences and to save others from having negative experiences as themselves. The present author thus proposes that the motivation of concern for other consumers, as induced by disconfirmation, may drive consumers to post online reviews and to publish review ratings that either exceed or are lower than their perceived quality to correct inaccurate online review ratings.

Hypothesis 4a (H4a): *The motivation of concern for other consumers mediates the impact of disconfirmation on consumers' willingness to post online reviews.*

Hypothesis 4b (H4b): *The motivation of concern for other consumers mediates the impact of disconfirmation on consumers' willingness to post online reviews with a small variance in prior online review ratings. This mediation process is attenuated among consumers facing a large variance in prior online review ratings.*

Hypothesis 4c (H4c): *The motivation of concern for other consumers mediates the impact of disconfirmation on consumers' online review rating decisions with a small variance in prior online review ratings. This mediation process is attenuated among consumers facing a large variance in prior online review ratings.*

Given these findings, the following research framework is proposed (see Figure 2.1).

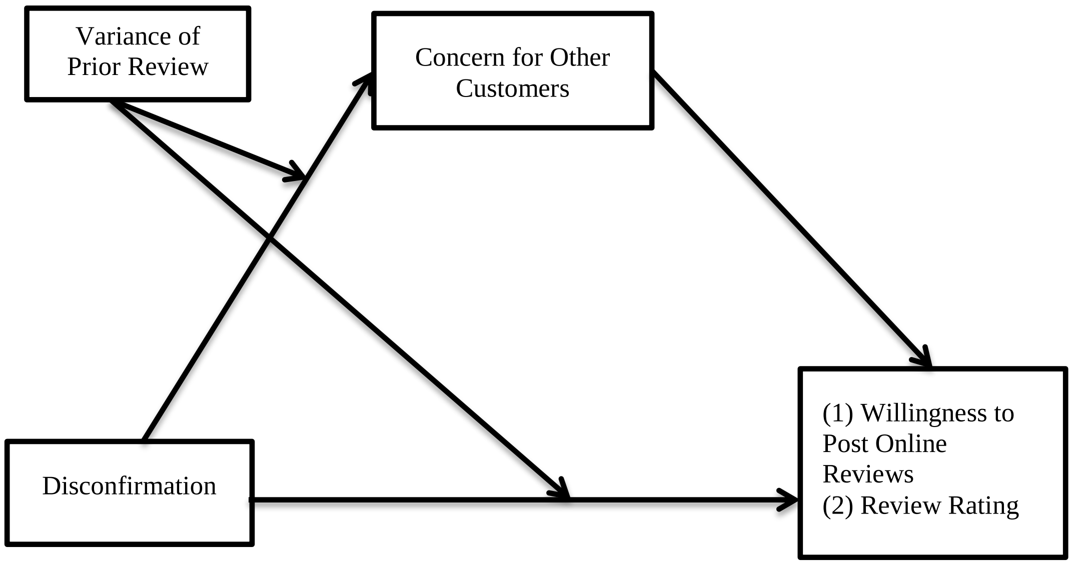

Figure 2.1 Research Framework

2.3 Empirical Overview

Three different experiments were conducted to test the above hypotheses. Experiment 1 was conducted in the hotel context to examine the influence of disconfirmation on consumers' willingness to post online reviews. Experiment 2 was completed in the restaurant context to examine the mediation effect of concern for other consumers on the influence of disconfirmation on consumers' willingness to post online reviews. Experiment 3 was carried out in the hotel context to examine (1) the influence of disconfirmation on consumers' review rating decisions; and (2) the moderating effect of prior review ratings' variance on the influence of disconfirmation on consumers' willingness to post online reviews and their review rating decisions.

2.4 Experiment 1

2.4.1 Design and Participants

Experiment 1 used a 2 (experience valence: positive vs. negative) × 3 (prior average review rating: none vs. 1.5 vs. 4.5) between-subjects experiment. To ensure an appropriate sample size, the author followed the criterion of at least 30 participants per cell, as 30 is a boundary between small and large samples (Hogg & Tanis, 1977); a similar criterion was applied in Wu et al. (2017). Therefore, a sample of 245 participants were recruited via Amazon Mechanical Turk, and they were randomly assigned to one of the above six conditions. Participants met the following criteria: U.S. residents, native English speakers, and 18 years or older. Mturk was used because of its low cost, demographic diversity, and similar degree of reliability compared with other data collection approaches (Buhrmester et al., 2011).

Regarding participant demographics, 49% were men, and 61.6% reported an annual household income of $40,000 or higher. In terms of age, 35.1% were 19–29 years old, 33.47% were 30–39, 14.69% were 40–49, 10.61% were 50–59, and 6.1% were 60 years or older. For education, nearly one-sixth (14.3%) had earned a high school degree or less, 37.1% had earned a college or associate degree, 40% possessed a bachelor’s degree, and 8.6% held a master’s or doctoral degree.

2.4.2 Stimuli and Procedures

First, participants read a short description about the hotel, depicting a scenario in which they had just stayed there for a vacation (see Table 2.1). Second, participants were exposed to experience valence manipulation, categorized into positive and negative experiences. In the condition of positive valence, participants were told their hotel experiences were quite good and much better than their expectations; in the condition of negative valence, participants were told their hotel experiences were extremely poor and much worse than expected (see Table 2.2 for stimuli). To test the validity of hotel experience manipulation, all participants were asked to rate their experiences in this hotel on a scale ranging from 1 = *terrible* to 5 = *excellent*.

Table 2.1 Hotel Description

Hotel description (Hotel name or hotel brand were not revealed to the participants)	Imagine that you just stayed at a hotel in Myrtle Beach for your vacation. The information of this hotel is as follows: Guests in this hotel will enjoy indoor and outdoor pools, free Wi-Fi, and continental breakfast. Balcony, microwave, and refrigerator are provided in all rooms. Moreover, the fitness center and laundromat are also available and provided to all guests in this hotel.

Table 2.2 Manipulation of Experience Valence

Positive experience	Imagine that you stayed at this hotel for three nights and had a fantastic and memorable experience. You are very satisfied with the hotel location, hotel service (such as quick check in and check out service), the room size, cleanness, room view and friendly staff. In fact, the hotel experience was very good and much better than you originally expected. Everything was wonderful to you!
Negative experience	Imagine that you stayed at this hotel for three nights and had a terrible and awful experience. You are very disappointed with the hotel location, hotel service (such as slow check in and check out service), the room size, cleanness, room view and unfriendly staff. In fact, the hotel experience was very bad and much worse than you originally expected. Everything was terrible to you!

Participants were then exposed to social influence manipulation, namely the average rating of prior reviews provided by other consumers (see Table 2.3). Participants were told, “This is the average rating of other consumers for this hotel, which is shown on the online review website.” This manipulation included three conditions: in the first, participants were not exposed to the prior average review rating; in the second and third, they were exposed to prior average review ratings (1.5 out of 5 and 4.5 out of 5, respectively).

Table 2.3 Manipulation of Prior Average Review Rating

Condition 1	No review rating information
Condition 2	After your hotel experience in Myrtle Beach, you find that other consumers' average rating for this hotel is shown on an online review website. The average rating is 1.5 out of 5.
Condition 3	After your hotel experience in Myrtle Beach, you find that other consumers' average rating for this hotel is shown on an online review website. The average rating is 4.5 out of 5.

After observing the average rating provided by other consumers, participants were told, "This online review website attracts a daily readership of 30,000, and people rely on these online reviews to make their own purchase decisions." Participants were then asked about their willingness to post online reviews: "Will you post your review for this hotel on the online review website?" (1 = yes, 0 = no). Demographic information was also collected from the participants as listed in Section 4.1.

2.4.3 Experiment 1 Results

Manipulation Check. Supporting the hotel experience manipulation, the participants assigned to a positive experience rated the hotel more favorably than those assigned to a negative hotel experience ($Mean_{positive} = 4.53$, $Mean_{negative} = 1.59$, *t*-test = 27.58, $p = 0.000$). Therefore, the valence manipulation worked as intended. Experimental results are summarized in Figure 2.2. The chi-square test shows that for the positive hotel experience scenario, the control group and the other two treatment groups exhibited significant differences in their willingness to post online reviews (Pearson χ^2 (2) = 15.712, p = 0.000; likelihood ratio (2) = 16.256, p = 0.000). Results indicate that a significantly higher proportion of participants were willing to post hotel reviews when their hotel experiences disconfirmed the prior average review rating (78.00%) compared to their counterparts whose hotel experiences confirmed the prior average review rating (52.8%).

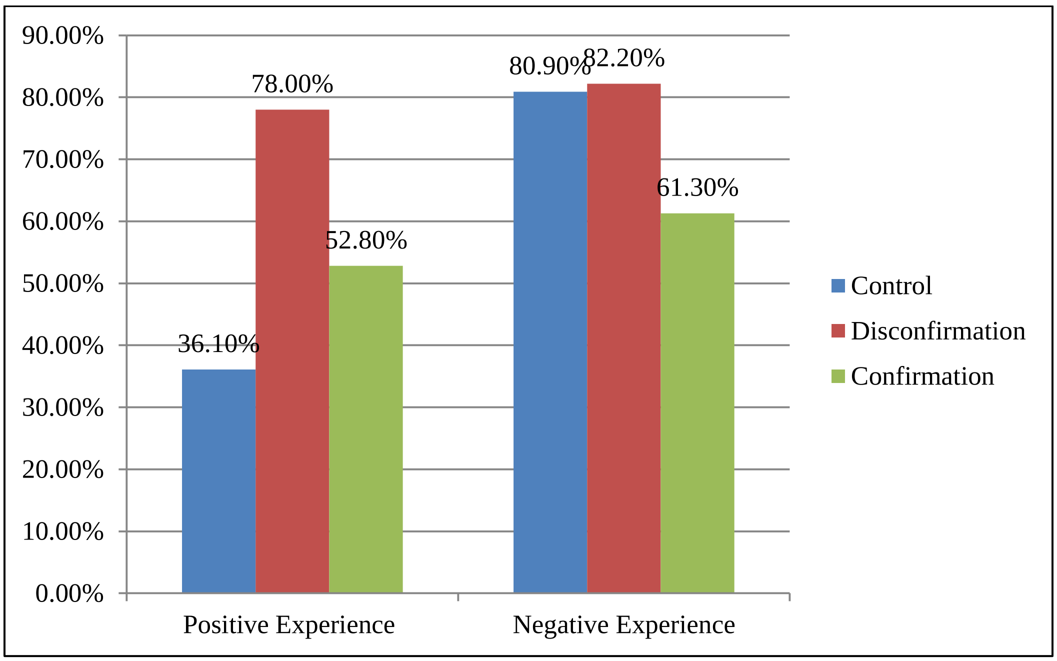

Figure 2.2 Effect of Disconfirmation on Consumers' Willingness to Post Online Reviews

Similarly, under the negative hotel experience scenario, the chi-square test (Pearson χ^2 (2) = 5.291, p = 0.071; likelihood ratio (2) = 4.946, p = 0.084) revealed significant differences among the control group and the other two treatment groups in terms of consumers' willingness to post online reviews. A significantly higher proportion of participants were willing to post hotel reviews when their hotel experiences disconfirmed the prior average review rating (82.20%) compared to their counterparts whose hotel experiences confirmed the prior average review rating (61.3%); therefore, H1 was supported.

Results also showed an asymmetrical effect between positive and negative hotel experiences. In the positive experience scenario, disconfirmation and confirmation each increased participants' willingness to post online reviews compared with the control group, although disconfirmation demonstrated a larger increase. This indicated that the simple presence of prior average review ratings led more participants to be willing to share their hotel experiences online, with the percentage increasing from 36.10% (control) to 52.80% (confirmation) and 78.00% (disconfirmation). However, in the negative experience scenario, disconfirmation did not increase participants' willingness to post online reviews, while confirmation decreased their intentions from 80.90% (control) to 61.30% (confirmation).

Moreover, the proportion of participants willing to post online reviews was much higher in the negative hotel experience condition (80.90%) than the positive condition (36.10%). The chi-square test (Pearson $\chi^2 = 17.225$, $p = 0.000$; likelihood ratio = 17.675, $p = 0.000$) indicated a significant difference, suggesting that consumers were more motivated to post reviews after having had a negative experience than a positive one.

2.4.4 Discussion

Experiment 1 provided empirical evidence regarding how the social influence of other consumers' average online hotel rating interacted with a subsequent consumer's own hotel experience (i.e., disconfirmation), thus influencing the consumer's willingness to post an online review. Results reveal that consumers were more willing to post online reviews when their personal hotel experiences disconfirmed the prior average review rating of the same hotel displayed on the online platform. On the other hand, consumers were more apt not to post online if their personal hotel experiences confirmed or were similar to the prior average review rating for the hotel. This result is consistent with that of Ho, Wu, and Tan (2017), who developed a hierarchical Bayesian model to analyze an online dataset from an e-commerce website. Their study demonstrated that a consumer's decision to post an online review was shaped by the degree of disconfirmation. However, Ho, Wu, and Tan's (2017) study did not (or cannot) indicate and verify whether consumers were aware of the disconfirmation between their own evaluation and prior average review ratings. The current study overcomes this limitation by using an experimental design method, and the findings contribute to the literature on factors influencing consumers' voluntary engagement in eWOM.

Moreover, participants were found to be more willing to post online reviews following a negative hotel experience than a positive experience. This finding may hold because compared with people with positive affect, those with negative affect exhibit a stronger tendency and motivation to find information to explain and alleviate their negative mood (Schwarz & Clore, 1983). By posting negative online reviews, consumers can reduce unpleasant affect while helping the online review community and subsequent potential consumers avoid a similarly dissatisfying experience (Grégoire, Tripp, & Legoux, 2009; Hornsey & Jetten, 2004).

2.5 Experiment 2

2.5.1 Design and Participants

Experiment 1 did not test consumers' motivation to post online reviews when encountering disconfirmation. Therefore, Experiment 2 was designed to test concern for others as the mediator for the influence of disconfirmation on consumers' willingness to post online reviews. This experiment employed a 2 (experience disconfirmation: confirmation vs. disconfirmation) × 2 (experience valence: positive vs. moderate) between-subjects experiment. To enhance the generalizability of the findings, hypotheses were tested in a restaurant service context. The validity of the manipulation/stimulus was also improved in this experiment compared to Experiment 1. Additionally, prior average review rating posted by other consumers were shown to participants post-consumption in Experiment 1; in Experiment 2, consumers were exposed to prior average review rating before purchase.

Using the criterion of 30 participants per cell, a sample of 216 people were recruited by Qualtrics, LLC and randomly assigned to one of the above four experimental conditions using the survey set-up on Qualtrics. Regarding participant demographics, 49.1% were men, and 54.2% reported an annual household income of $40,000 or higher. For age, 8.8% were 19–29 years old, 17.6% were 30–39, 13% were 40–49, 18.9% were 50–59, 30.1% were 60–69, and 11.6% were 70 or older. In terms of education, about a quarter (25.5%) possessed a high school degree or less, 31% had earned a college or associate degree, 33.3% possessed a bachelor's degree, and 10.2% held a master's or doctoral degree. Caucasians were the most common ethnicity (87%).

2.5.2 Stimuli and Procedures

To manipulate experience disconfirmation, participants were provided with a scenario that they had recently dined in a hypothetical restaurant, Franco's. Before dining in this restaurant, participants were asked to imagine they had checked an online review website called "RestaurantFinder" and noticed either a moderate (3 out of 5 stars) or positive (5 out of 5 stars) consensus rating for Franco's (see Figures 2.3 and 2.4 for stimuli). After checking the online reviews, participants decided to dine at the restaurant. Then participants were given a scenario that they had either a moderate or a positive dining experience. In the positive experience condition, participants were told, "Your dining experiences were excellent. Everything in the restaurant, including the food, service, and environment, was perfect!" In the moderate experience condition, participants were told, "Your dining experiences were just OK. The food and the service were average."

Next, participants were asked questions related to the motivation of concern for others to post online reviews for the restaurant and questions regarding their willingness to post online reviews. Demographic information and details about participants' prior review-writing experience were also collected.

Figure 2.3 Stimuli of a Moderate Consensus Rating for Franco's

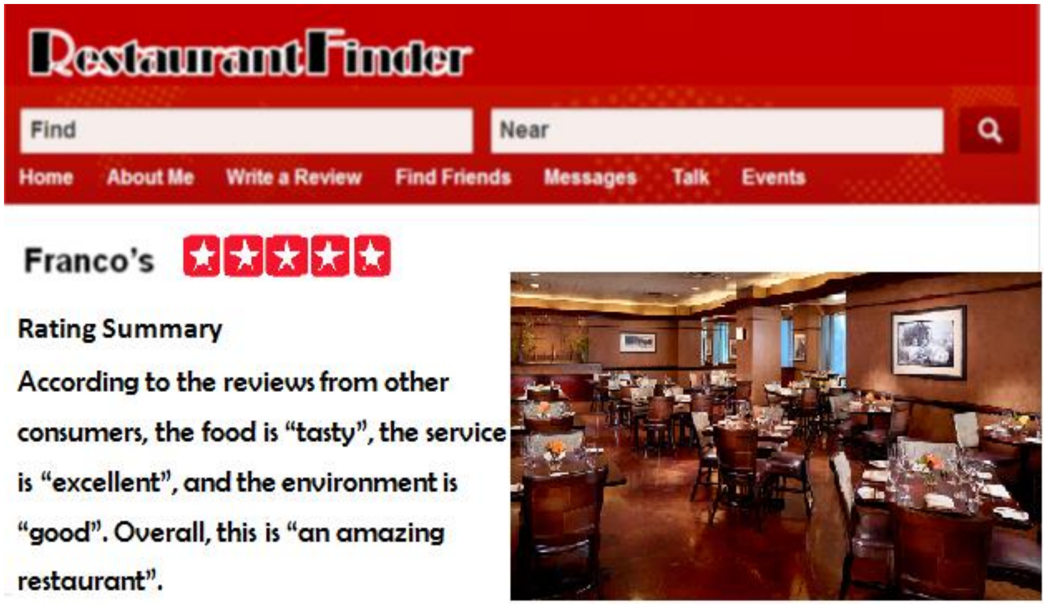

Figure 2.4 Stimuli of a Positive Consensus Rating for Franco's

2.5.3 Measures

Table 2.4 Measurement of Concern for Other Consumers

Concern for Others (Positive Experience)
If I share my experience at Franco's on the review website…
1) It will tell others that restaurant Franco's is not as the review claims.
2) It will help others with my own positive experience.
3) It will give others the opportunity to choose the right restaurant.
Concern for Others (Moderate Experience)
If I share my experience at Franco's on the review website…
1) It will warn others that restaurant Franco's is not as the review claims.
2) It will warn others of my bad experience.
3) It will save others from having the same negative experiences as me.
4) It will give others the opportunity to choose the right restaurant.

Adopted from Hennig-Thurau et al. (2004), the motivation of concern for other consumers was measured using a 7-point Likert scale ranging from 1 = *strongly disagree* to 7 = *strongly agree* (see Table 2.4). The measurement of consumers' willingness to post online reviews was adopted from Wu et al. (2017) by asking participants to answer, “Are you interested in saying something on the online review website ‘RestaurantFinder’ about your own experience at the restaurant?” using a 7-point Likert scale (1 = *not interested at all*, 7 = *very interested*) and “Are you willing to write a review on the online review website ‘RestaurantFinder’ about your dining experience in the restaurant?” using a 7-point Likert scale (1 = *not at all willing*, 7 = *very much willing*).

2.5.4 Experiment 2 Results

Manipulation Check. To verify the effectiveness of the manipulation, participants were asked to answer two true-or-false questions: “In the above scenario, my dining experience at Franco’s was excellent” and “In the above scenario, my dining experience at Franco’s was similar to the prior online reviews I saw.” All participants included in the formal data analysis passed these two questions.

Table 2.5 Impact of Disconfirmation and Experience Valence on Consumers’ Willingness to Post Online Reviews

	Coefficient	SE	T	*p*-value	95% CI	
Constant	1.9710	.6136	3.2122	.0015	.7614	3.1807
Covariates						
Gender	.2041	.1945	1.0495	.2952	-.1793	.5876
Age	-.0004	.0066	-.0654	.9479	-.0134	.0126
Review frequency	.8524	.1017	8.3811	.0000	.6519	1.0529
Test effects						
Disconfirmation	0.5565	.2813	1.9785	.0492	.0020	1.1109
Experience valence	0.6659	.2669	2.4949	.0134	.1397	1.1921
Valence × Disconfirmation	-0.0379	.3928	-.0966	.9231	-.8122	.7363

R^2 increase due to interaction: R^2 = 0.0000; [F (1, 209) = .0093, *p* = .9231]

Model summary: R^2 = 0.3323; [F (6, 209) = 17.3392, *p* = 0.0000]

H1 posits that consumers' willingness to post online reviews is influenced by disconfirmation. To test H1 along with the possible moderating effect of experience valence on disconfirmation influence, Model 1 in Hayes's (2013) PROCESS procedure was employed to analyze the interaction effects between two dichotomous variables. The estimation result is shown in Table 2.5, indicating a significant main effect of disconfirmation on customers' willingness to post online reviews at a 95% significance level (b = 0.5565, p = 0.0492); however, the interaction effect between experience valence and disconfirmation was insignificant ($b_{V \times D}$ = -0.0379, p = 0.9231). To have a good understanding of the interaction effect, the effects of disconfirmation and experience valence on consumers' willingness to post online reviews are illustrated in Figure 2.5. Overall, H1 was supported.

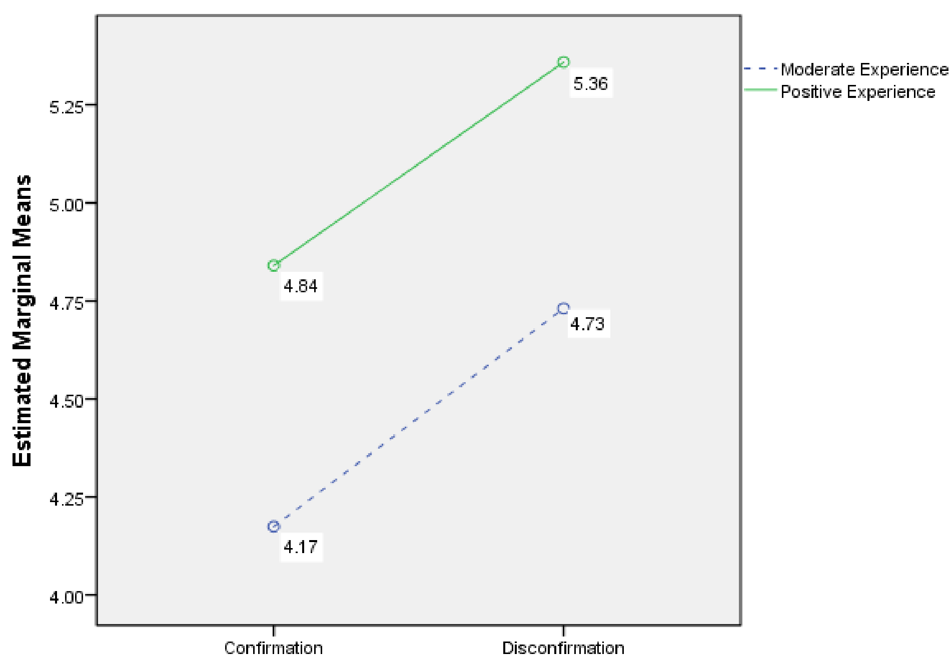

Figure 2.5 Effects of Disconfirmation and Experience Valence on Consumers' Willingness to Post Online Reviews

H4a proposes that concern for other consumers will mediate the impact of disconfirmation on consumers' willingness to post online reviews. A moderated mediation analysis was conducted to see did a mediation effect exist in the positive experience group and moderate experience group. Model 8 in Hayes's (2013) PROCESS procedure was applied for this purpose, using disconfirmation as the independent variable, concern for others as a mediator, experience valence (positive vs. moderate) as the moderator, and willingness to post online reviews as the dependent variable. Based on 10,000 bootstrap samples, the bias-corrected bootstrapping technique was applied to test the above conditional indirect effect.

As shown in Figure 2.6, the conditional direct effect of disconfirmation on participants' willingness to post online reviews was insignificant when participants had either a moderate experience ($b = 0.2015$, $p = 0.4475$) or positive experience ($b = -0.1376$, $p = 0.6133$). The test for equality of the conditional direct effects in the two groups revealed no significant difference in the above direct effects between the moderate experience group and positive experience group (disconfirmation × experience valence = -0.3390, $p = 0.3530$).

By contrast, the conditional indirect effect of disconfirmation on participants' willingness to post online reviews through concern for other consumers was significant for participants with a moderate experience ($b = 0.3550$, 95% boot CI: 0.1262, 0.6531) as evidenced by the confidence interval not including zero. The effect was also significant and even stronger for participants with a positive experience ($b = 0.6561$, 95% boot CI: 0.3988, 0.9941). The test of equality of the conditional indirect effects in the two groups shows a significant difference of the above indirect effects between the moderate experience group and positive experience group (index of moderated mediation = 0.3011, 95% boot CI: 0.0051, 0.6845). These results substantiated the hypothesized conditional indirect effect through concern for other consumers; thus, H4a was supported.

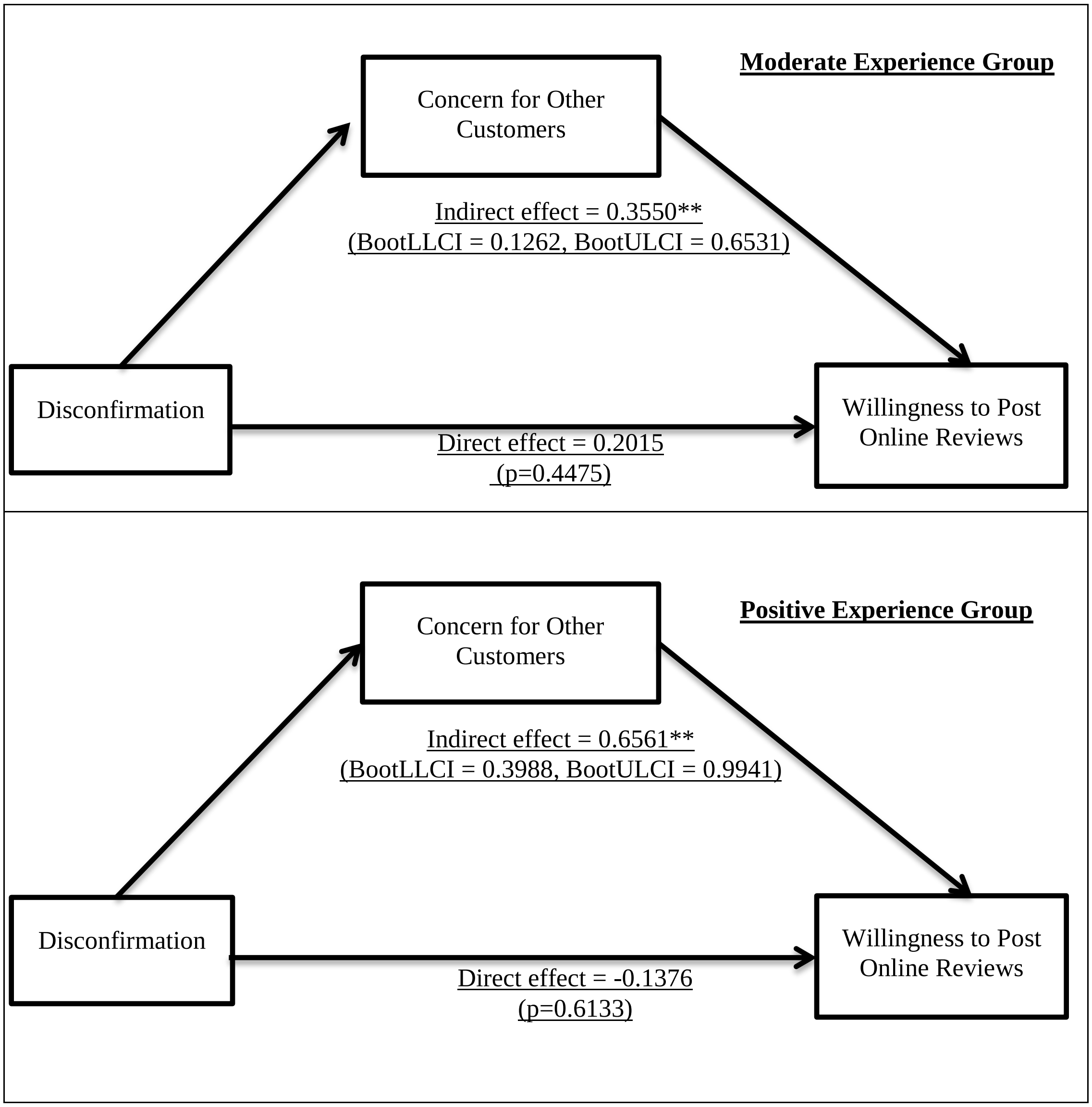

Figure 2.6 Results of Mediation Model for Positive Experience and Moderate Experience

2.5.5 Discussion

Experiment 2 introduced empirical evidence regarding how disconfirmation influences consumers' willingness to post online reviews. Results indicated three major findings. First, most previous research assumed that prior reviews posted by other consumers would only influence subsequent consumers' willingness to post reviews and review rating decisions after purchase (Moe & Schweidel, 2012; Schlosser, 2005). However, Ho, Wu, and Tan (2017) asserted that the social influence of prior reviews can also occur when subsequent consumers gather information prior to making a purchase. In Experiment 1, participants were shown prior average review ratings posted by other consumers after making a purchase but prior to purchase in Experiment 2. After changing the timing of the social influence (i.e., prior average review rating), the estimation results of Experiment 2 indicated that consumers' willingness to post online reviews for a restaurant increased as their post-consumption evaluation deviated further from the prior average review rating. The influence of disconfirmation therefore appeared consistent across these two experiments regardless of the order in which consumers were exposed to social influence.

Second, the significant positive influence of disconfirmation on consumers' willingness to post online reviews only happens through the increased motivation of concern for other consumers, which serves as a mediator in the relationship between disconfirmation and willingness to post online reviews. When consumers experienced positive disconfirmation, they were more likely to write online reviews to help others by describing a personally positive experience and to assist others in choosing the right restaurant. By contrast, when consumers encountered negative disconfirmation, they tended to write online reviews to warn others of a poor experience and to save them from enduring the same fate. Experiment 1 tested the direct effect, which included all possible factors that could influence the relationship between disconfirmation and consumers' willingness to post online reviews. Experiment 2 further clarified this mechanism, namely the mediating effect of “concern for others” in the relationship between disconfirmation and consumers’ willingness to post online reviews.

Third, the indirect effect of disconfirmation on consumers’ willingness to post online reviews through concern for others was moderated by the valence of consumer experience. Ho, Wu and Tan’s (2017) study suggested that consumers’ willingness to post online reviews is affected by negative disconfirmation to a larger extent than positive disconfirmation. Different from their research, Experiment 2 revealed that the disconfirmation effect on consumers’ willingness to post online reviews was stronger for participants with positive experiences than for those with moderate experiences.

2.6 Experiment 3

2.6.1 Design and Participants

Experiment 3 tested the effect of disconfirmation on consumers’ online review rating decisions as well as the moderating role of prior review ratings’ variance on the influence of disconfirmation on consumers’ willingness to post online reviews and review rating decisions. This experiment used a 2 (experience disconfirmation: confirmation vs. disconfirmation) × 2 (prior review ratings’ variance: low variance vs. high variance) between-subjects experiment. Hypotheses were tested in a hotel context.

Using 30 participants per cell, a sample of 274 participants were recruited from Qualtrics, LLC and randomly assigned to one of the above four experimental conditions using the survey set-up on Qualtrics. In terms of demographics, 53.3% of participants were men, and 54.4% reported an annual household income of $40,000 or higher. About an eighth (13.5%) were 19–29 years old, 16.4% were 30–39, 11.3% were 40–49, 17.9%

were 50–59, 25.9% were 60–69, and 15% were 70 or older. In terms of education, 20.4% had a high school degree or less, 36.1% had some college or an associate degree, 31% participants held a bachelor's degree, and 12.4% possessed a master's or doctoral degree. The sample was predominantly Caucasian (88.7%).

2.6.2 Stimuli and Procedures

Initially, participants were given a scenario that they recently stayed at a hotel, Le Bleu, for a vacation. Participants were told they received "an above average experience" and "a good value for the money" although the hotel could improve in some aspects. Then, participants were asked to imagine they checked the online review website "HotelsCombined" after their stay and found either a positive (7 out of 10 stars) or negative (4 out of 10 stars) average rating for Le Bleu (see Figures 2.7 and 2.8). Afterwards, participants were shown the dispersion of prior review ratings posted by past consumers. Participants were randomly assigned to either of the following two conditions: (1) high dispersion (variance = 10.9) for Le Bleu; or (2) low dispersion (variance = 0.9; see Figures 2.9 and 2.10, adopted from He and Bond [2015]).

Similar to Experiment 2, following the above scenarios, participants were asked questions related to the online review-posting motivation of concern for others along with questions related to their willingness to post online reviews (for measures, please refer to Section 5.3). Participants were also asked to rate Le Bleu on a scale ranging from 1 star (extremely bad) to 10 stars (extremely good), as if they were posting the rating on "HotelsCombined." Demographic information and participants' prior review-writing experience were also collected.

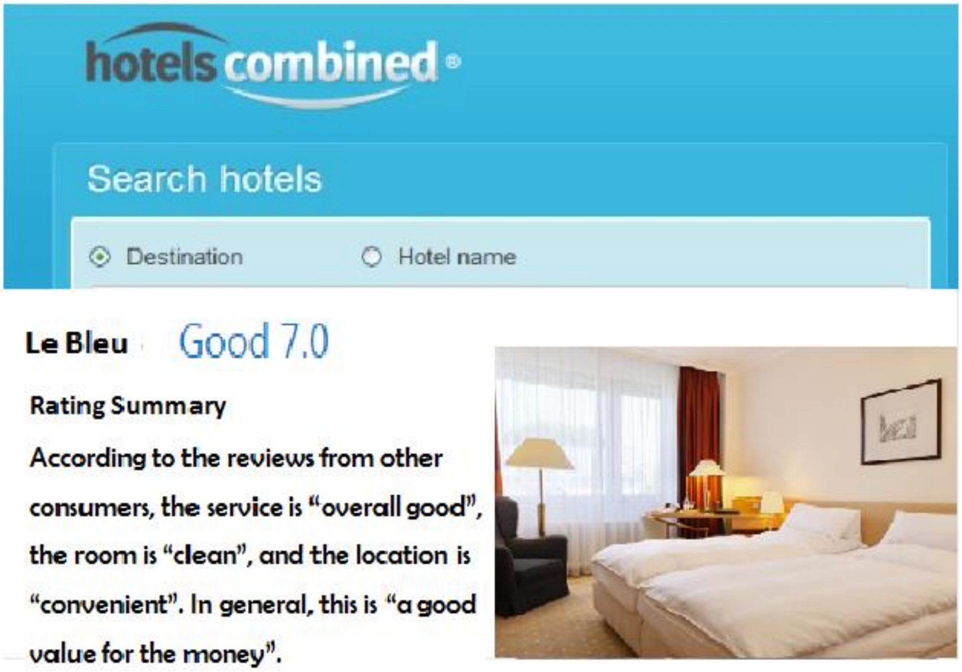

Figure 2.7 Stimuli of a Positive Consensus Rating for Le Bleu

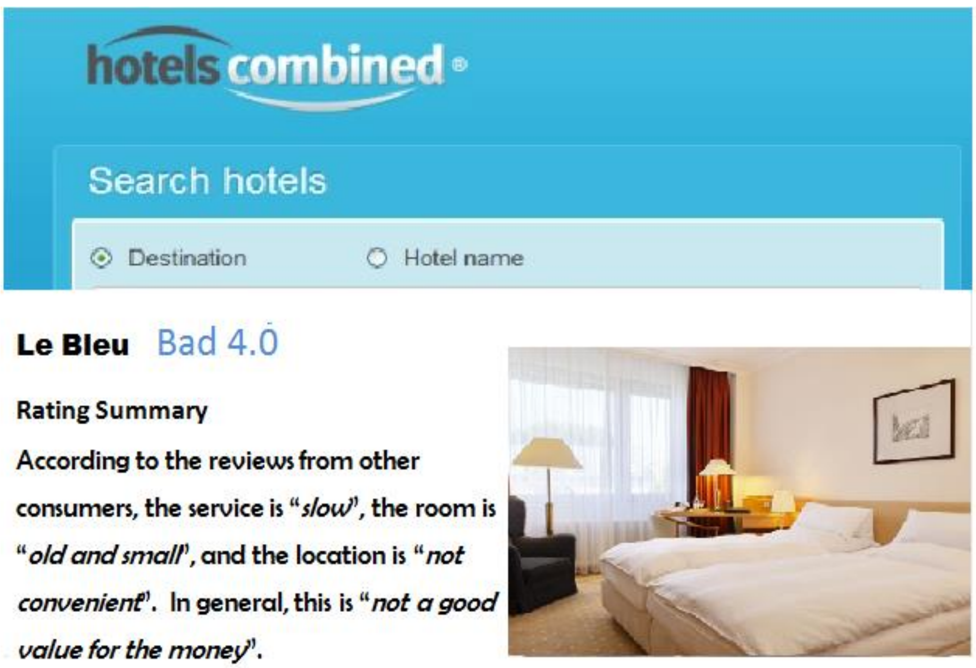

Figure 2.8 Stimuli of a Negative Consensus Rating for Le Bleu

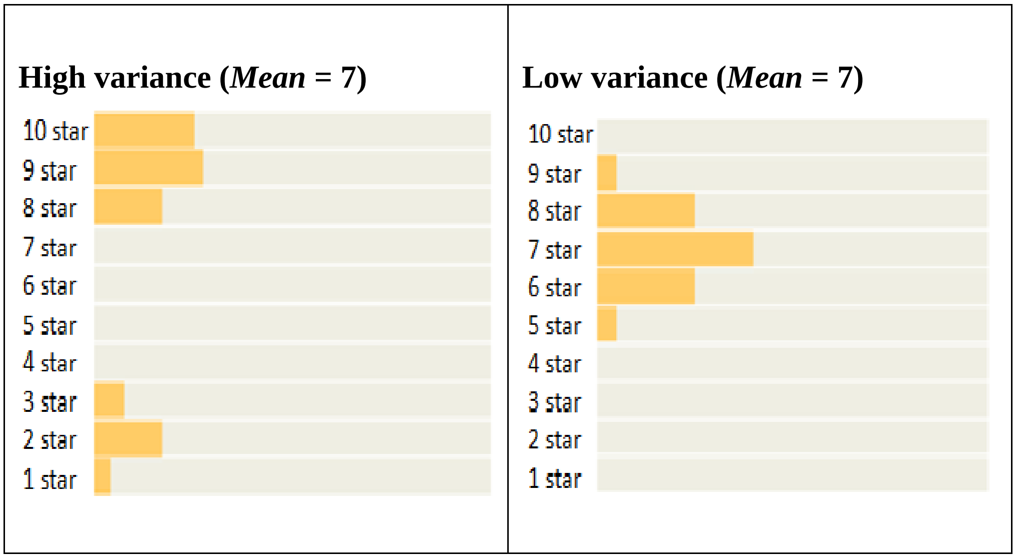

Figure 2.9 Stimuli of High and Low Prior Ratings' Variance under Positive Rating Scenario

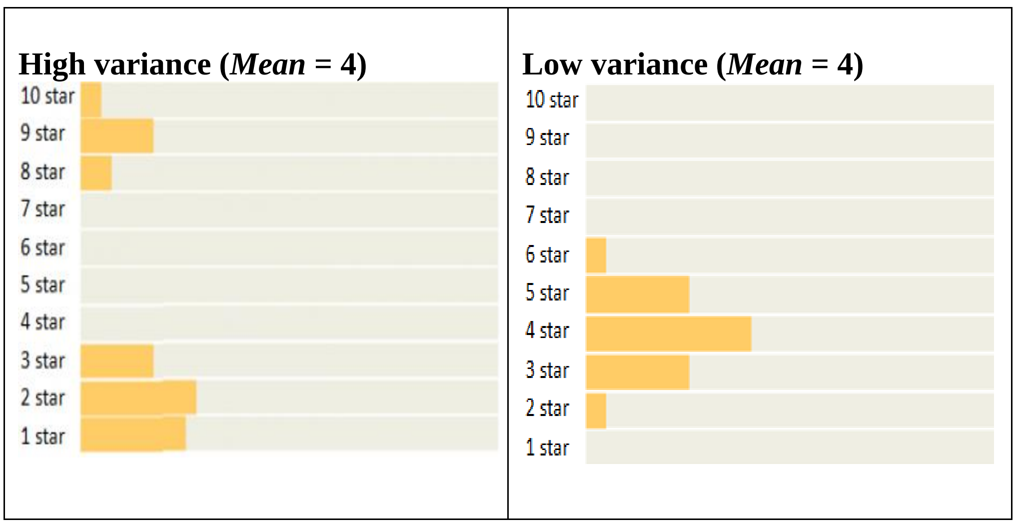

Figure 2.10 Stimuli of High and Low Prior Ratings' Variance under Negative Rating Scenario

2.6.3 Experiment 3 Results on Consumers' Willingness to Post Online Reviews

Manipulation check. Similar to Experiment 2, to verify the effectiveness of the disconfirmation manipulation, participants were asked to answer two true-or-false questions: “In this scenario, my experience at Le Bleu hotel was overall good” and “In this scenario, my experience at Le Bleu hotel was similar to the prior reviews.” All participants included in formal data analysis passed these questions. To verify the manipulation effectiveness of the variance in prior review ratings, participants were asked to answer the question, “Based on the above description of online reviews, to what extent do past consumers agree with each other in general?” on a 5-point Likert scale (1 = *strongly disagree,* 5 = *strongly agree*). Results indicate that participants perceived the stimuli as intended ($\text{Mean}_{\textit{Low-variance}} = 4.23$; $\text{Mean}_{\textit{High-variance}} = 1.64$; $t = 47.261$, $p = 0.000$).

Table 2.6 Impact of Disconfirmation and Variance of Prior Review Ratings on Consumers’ Willingness to Post Online Reviews

	Coefficient	SE	*T*	*p*-value	95% CI	
Constant	3.1040	.4565	6.7994	.0000	2.2052	4.0029
Covariates						
Gender	-.1239	.1599	-.7750	.4390	-.4387	.1909
Age	-.0045	.0048	-.9378	.3492	-.0139	.0049
Review Frequency	.6881	.0792	8.6831	.0000	.5321	.8441
Test effects						
Disconfirmation	.9424	.2088	4.5127	.0000	.5312	1.3536
Variation	.4530	.2190	2.0683	.0396	.0218	.8843
Disconfirmation × Variation	-.3118	.3213	-.9703	.3328	-.9444	.3209

R^2 increase due to interaction: $R^2 = 0.0025$; [F (1, 267)= 0.9414, $p = 0.3328$]
Model summary: $R^2 = .2857$; [F (6, 267) = 17.8004, $p = 0.0000$]

H3a presumed a two-way interaction effect between disconfirmation and prior review ratings’ variance on customers’ willingness to post online reviews. Model 1 in Hayes’s (2013) PROCESS procedure was applied to test this hypothesis. The estimation results (see Table 2.6) reveal a significant main effect of disconfirmation on consumers’ willingness to post online reviews at a 95% significance level ($b = 0.9424$, $p < 0.01$).

However, the moderating effect of the variance in prior review ratings on the influence of disconfirmation was insignificant ($b_{D \times V}$ = -0.3118, p = 0.3328). In addition, the variance of prior review ratings showed a positive and significant impact on consumers' willingness to post online reviews at a 95% significance level (b = 0.4530, p = 0.0396), suggesting that dissentious rating environments can encourage consumers to post online reviews. To have a good understanding of the interaction effect, the effects of disconfirmation and variance on consumers' willingness to post online reviews are illustrated in Figure 2.11. Ultimately, H1 was supported and H3a was not.

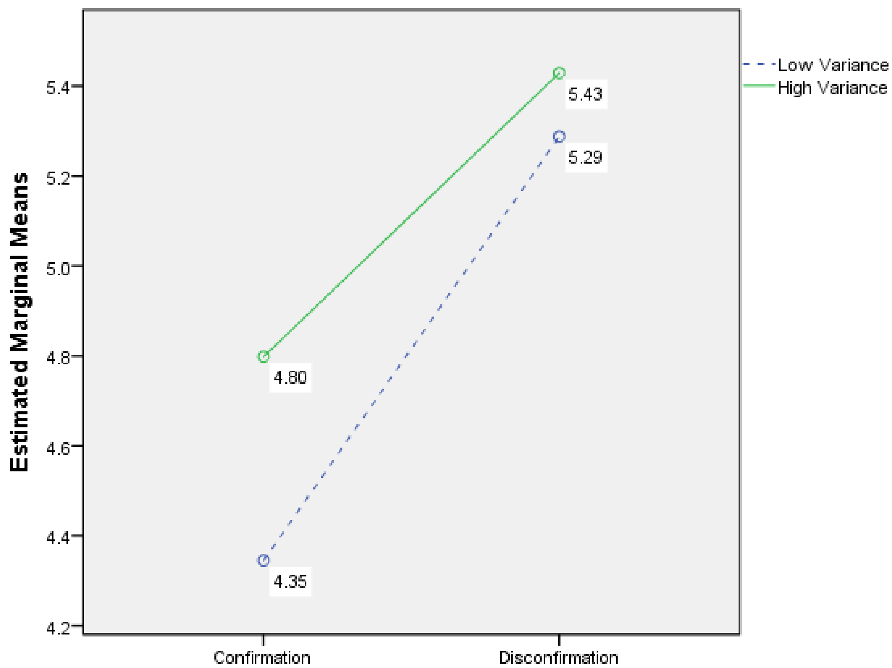

Figure 2.11 Effects of Disconfirmation and Variance on Consumers' Willingness to Post Online Reviews

H4b predicts that the effect of disconfirmation on participants' willingness to post online reviews is conditionally mediated by concern for other consumers. A moderated mediation analysis of Model 8 in Hayes's (2013) PROCESS procedure was applied to test this hypothesis, using disconfirmation as the independent variable, variance of prior review ratings as the moderator, concern for others as a mediator, and willingness to post an online review as the dependent variable. Based on 10,000 bootstrap samples, the bias-corrected bootstrapping technique was applied to examine the conditional indirect effect.

As shown in Figure 2.12, the conditional direct effect of disconfirmation on participants' willingness to post online reviews was insignificant when prior review ratings' variance was low (b = 0.2012, p = 0.3535) and when prior review ratings' variance was high (b = 0.1517, p = 0.5119). The test of equality of the conditional direct effects in the two groups shows no significant difference in the above direct effects between low- and high-variance groups (disconfirmation × variance = -0.0496, p = 0.8672).

Moreover, the conditional indirect effect of disconfirmation on participants' willingness to post online reviews through concern for other consumers was significant when the variance of prior review ratings was high (b = 0.4790, 95% boot CI: 0.2644, 0.7498), given that this confidence interval does not include zero. The effect was also significant and even stronger for participants when the variance of prior review ratings was low (b = 0.7412, 95% boot CI: 0.4622, 1.0609). The test of equality of the conditional indirect effects in the two groups demonstrated a significant difference in the above indirect effects between high- and low-variance groups (index of moderated mediation = -0.2622, 95% boot CI: -0.5623, -0.0203), substantiating the hypothesized conditional indirect effect through concern for other consumers; therefore, H4b was supported.

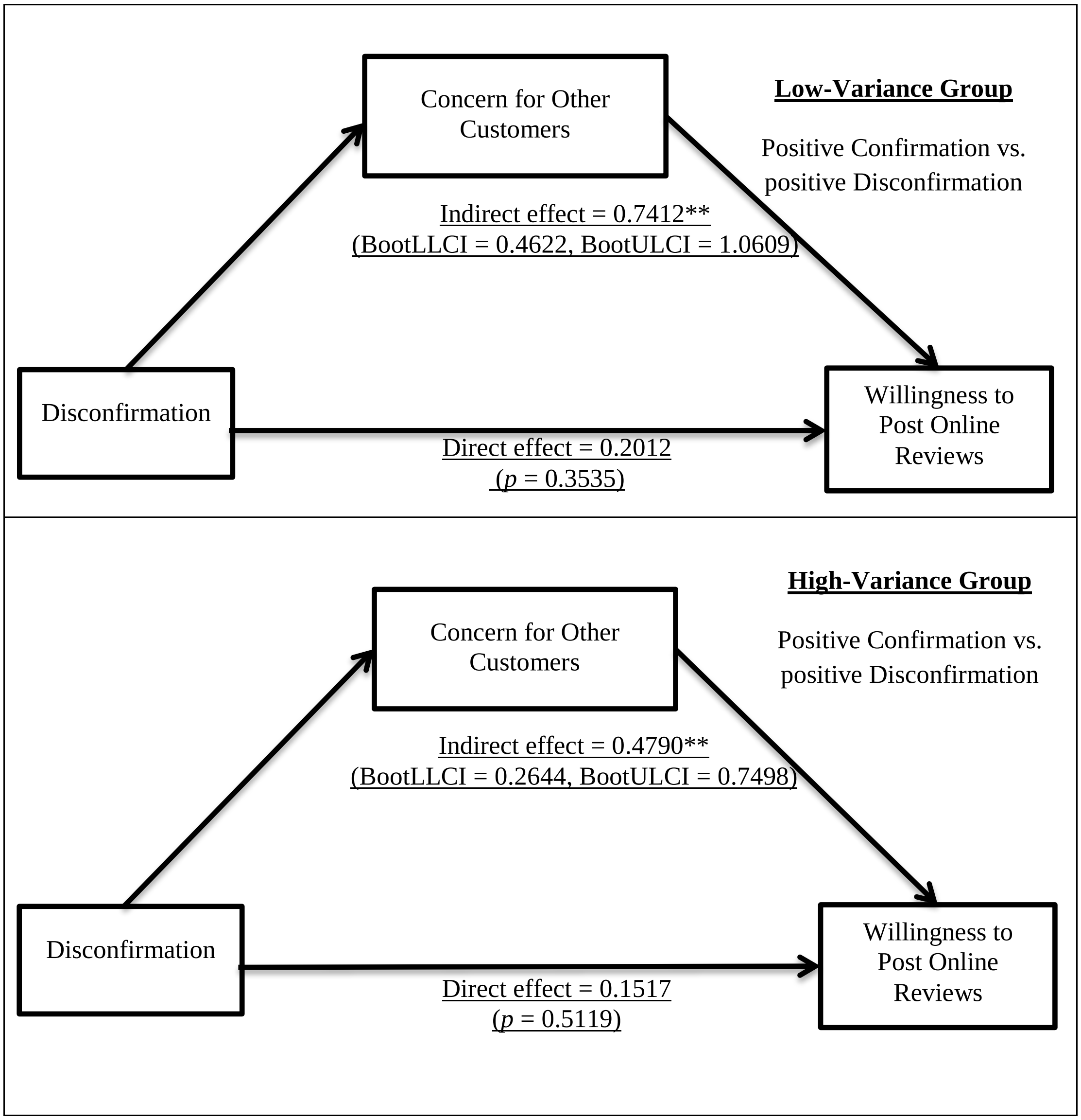

Figure 2.12 Results of Moderated Mediation Model

2.6.4 Experiment 3 Results on Consumers' Online Review Rating Decisions

H2 states that a consumer's online review rating decision is influenced by disconfirmation, and H3b posits a two-way interaction effect exists between disconfirmation and variance of prior review ratings on customers' online review rating decisions. Model 1 in Hayes's (2013) PROCESS procedure was used to test these hypotheses. Estimation results are shown in Table 2.7, indicating a significant main effect of disconfirmation on consumers' review rating decisions at a 95% significance level (b = 0.5726, $p < 0.01$). However, an insignificant interaction effect was found for disconfirmation by prior review ratings' variance on participants' online review rating decisions ($b_{D\ xV}$ = -0.3571, p = 0.1802). The variance of prior review ratings demonstrated a positive and significant impact on consumers' review ratings at a 95% significance level (b = 0.3710, p = 0.0415), implying that dissentious rating environments compelled consumers with positive hotel experiences to post higher review ratings. To better understand the two-way interaction effect, the effects of disconfirmation and variance on consumers' review rating decisions are presented in Figure 2.13. In all, H2 was supported and H3b was not.

Table 2.7 Impact of Disconfirmation and Variance of Prior Review Ratings on Consumers' Online Review Rating Decisions

	Coefficient	SE	*T*	*p*-value	95% CI	
Constant	7.7266	.3776	20.4630	.0000	6.9832	8.4701
Covariates						
Gender	-.1110	.1322	-.8394	.4020	-.3713	.1493
Age	-.0074	.0040	-1.8599	.0640	-.0152	.0004
Review Frequency	.1673	.0655	2.5518	.0113	.0382	.2963
Test effects						
Disconfirmation	.5726	.1727	3.3152	.0010	.2325	.9127
Variation	.3710	.1812	2.0479	.0415	.0143	.7277
Disconfirmation × Variation	-.3571	.2658	-1.3437	.1802	-.8804	.1662

R^2 increase due to interaction: R^2 = .0062; [F (1, 267) = 1.8055, p = .1802]

Model summary: R^2 = .0863; [F (6, 267) = 4.2012, p = 0.0005]

H4c proposes that the effect of disconfirmation on participants' online review rating decisions is conditionally mediated by concern for other consumers. Model 8 in Hayes's (2013) PROCESS procedure was conducted for a moderated mediation analysis to test H4c with disconfirmation as the independent variable, variance of prior review ratings as the moderator, concern for other consumers as a mediator, and participants' online review ratings as the dependent variable. Based on 10,000 bootstrap samples, the above conditional indirect effect was tested by using the bias-corrected bootstrapping technique.

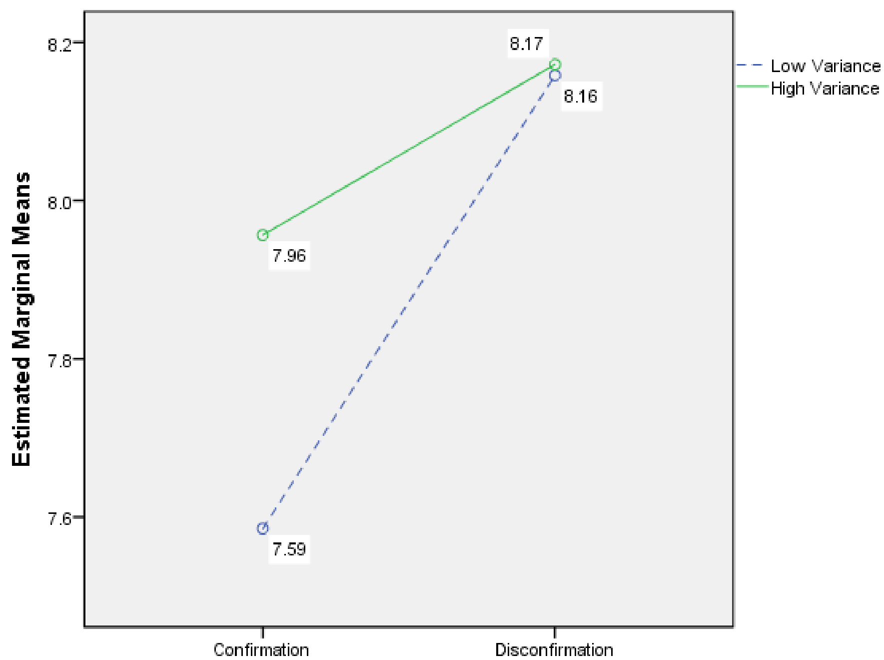

Figure 2.13 Effects of Disconfirmation and Variance on Consumers' Online Review Rating Decisions

As shown in Figure 2.14, the conditional direct effect of disconfirmation on participants' online review ratings was insignificant regardless of whether the variance of prior review ratings was low (b = 0.2012, p = 0.2907) or high (b = -0.0245, p = 0.9037). The test of equality of the conditional direct effects in the two groups revealed no significant difference in the above direct effects between low- and high-variance groups (disconfirmation × variance = -0.2257, p = 0.3860).

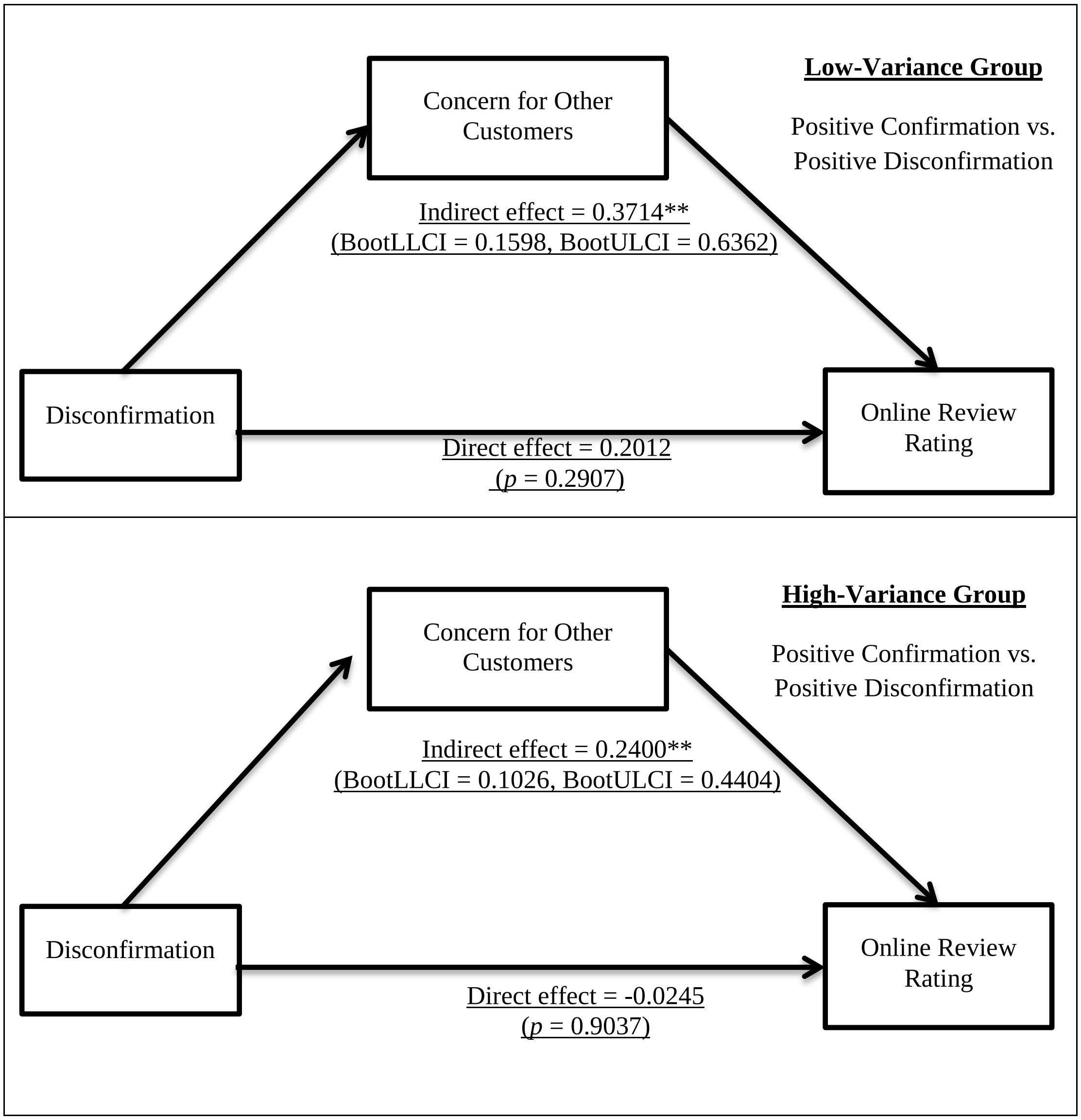

Figure 2.14 Mediation Path

Figure 2.14 also demonstrates that the conditional indirect effect of disconfirmation on participants' online review ratings through concern for other consumers was significant when the variance of prior review ratings was high (*b* = 0.2400, 95% boot CI: 0.1026, 0.4404). The effect was significant and much stronger for participants when the variance of prior review ratings was low (*b* = 0.3714, 95% boot CI: 0.1598, 0.6362). The test of equality of the conditional indirect effects in the two groups shows a significant difference in the above indirect effects between high- and low-variance groups (index of moderated mediation = -0.1314, 95% boot CI: -0.3422, -0.0133). These results support the hypothesized conditional indirect effect through concern for other consumers; therefore, H4c was supported.

2.6.5 Discussion

Experiment 3 offered empirical evidence regarding the influence of hotel disconfirmation on consumers' online review rating decisions and the role of prior review ratings' variance on the impacts of disconfirmation on consumers' willingness to post online reviews and review rating decisions. Three findings warrant further attention. First, positive disconfirmation (vs. positive confirmation) was found to lead to higher consumer review ratings. A consumer may post a rating above the mean when he/she experiences positive disconfirmation, whereas a consumer may leave a lower rating to warn others of a poor experience when facing negative disconfirmation. This result is consistent with Ho, Wu, and Tan's (2017) study, which found that the disconfirmation between a person's expectations and experienced product quality influenced his/her rating decision. However, Ho, Wu, and Tan's (2017) study assumed a consumer would read prior average review ratings before purchase, although they could not empirically verify this assumption. To address this limitation, the present study employed an experimental design to ensure participants were aware of disconfirmation by seeing the prior average review rating. Then, a manipulation check was conducted to make sure participants acknowledged disconfirmation or confirmation by comparing their experienced hotel quality to the prior average review rating.

Second, the variance of prior review ratings can increase consumers' willingness to post online reviews for hotels. In other words, dissentious rating environments can encourage consumers to post online reviews. This result is consistent with Lee, Hosanagar, and Tan's (2015) study, which also revealed that the impact of rating environments, especially the variance of prior online review ratings, can significantly affect subsequent consumers' review-posting propensity for films.

Third, the indirect effects of disconfirmation on consumers' willingness to post online reviews and review ratings were stronger for prior review ratings with a lower variance than for those with a higher variance. This finding implies that the variance of prior review ratings accentuates the disconfirmation effect, which certainly enriches the online review social influence literature and EDT.

2.7 Conclusion and Discussion

2.7.1 General Conclusion

This study empirically tested the disconfirmation effects on consumers' willingness to post online reviews and review rating decisions in hotel and restaurant contexts. The empirical results of three different experiments show that disconfirmation can significantly influence consumers' willingness to post online reviews and review ratings through the mechanism of concern for others. Moreover, this study delineated the moderating effect of prior review ratings' variance on disconfirmation effects. Table 2.8 summarizes the hypotheses testing results.

2.7.2 Implications

This study contributes to the literature in several ways. First, scholars have only recently begun to examine the social influence of prior reviews on subsequent consumers' online review behavior for the same product. The findings of the three experiments herein contribute to this emerging topic and indicate that consumers' willingness to post online reviews and online review ratings are influenced by disconfirmation in hotel and restaurant contexts. This study also enhances the literature on social influence and online review-posting behavior.

Table 2.8 Summary of Hypotheses Testing Results

Hypotheses	**Empirical Support**
H1: Disconfirmation (vs. confirmation) leads to increased willingness to post online reviews.	√
H2: Disconfirmation (vs. confirmation) has a significant impact on consumers' online review ratings.	√
H3a: The variance of prior ratings moderates the direct influence of disconfirmation on consumers' willingness to post online reviews; the influence is stronger when the variance of prior ratings is smaller and weaker when the variance is larger.	×
H3b: The variance of prior ratings moderates the direct influence of disconfirmation on consumers' online review rating decisions; the influence is stronger when the variance of prior ratings is smaller and weaker when the variance is larger.	×
H4a: The motivation of concern for other consumers mediates the impact of disconfirmation on consumers' willingness to post online reviews.	√
H4b: The motivation of concern for other consumers mediates the impact of disconfirmation on consumers' willingness to post online reviews with a small variance in prior online review ratings; this mediation process is attenuated among consumers facing a large variance in prior online review ratings.	√
H4c: The motivation of concern for other consumers mediates the impact of disconfirmation on consumers' online review rating decisions with a small variance in prior online review ratings; this mediation process is attenuated among consumers facing a large variance in prior online review ratings.	√

Second, prior literature has studied the relationship between disconfirmation and satisfaction fairly extensively, whereas the influence of disconfirmation on consumer post-consumption online review behavior remains scarcely researched. This study examined the disconfirmation effects on consumers' willingness to post online reviews and their review rating decisions. Findings enhance the present understanding of online review disconfirmation and its influences and contribute to the literature on the relationship between disconfirmation and consumer post-satisfaction behavior.

Third, Cheung and Lee (2012) emphasized the need for additional studies regarding consumers' eWOM motives. This study is the first to empirically investigate the underlying motivations behind the decision to post online reviews and review ratings from a social influence angle, thereby expanding the eWOM motivation literature.

Fourth, this study identified several important factors that can moderate the effects of disconfirmation on consumers' willingness to post online reviews and their review rating decisions. Findings deepen the understanding of online review disconfirmation and its influences.

This study also provides several important managerial implications to marketers and managers regarding online review management as well as the issues surrounding online review manipulation and its consequences. Findings of this study provide meaningful insights for product marketers who may manipulate online reviews and ratings by posting deceptive positive evaluations of their own products and fabricating negative reviews and ratings about their competitors. Although inflated ratings and positive reviews can increase the number of customers and overall hotel or restaurant revenue in the short run, such measures also increase the likelihood of a consumer encountering a certain degree of disconfirmation in the long run. Perceived disconfirmation will lead to customers more motivated to post online reviews. Negatively disconfirmed consumers tend to post review ratings that are lower than their actual experiences to compensate for manipulated review ratings. Disconfirmed consumers may also experience normative conflict and write extremely negative reviews that may even include offensive language to express their disappointment and dissatisfaction, resulting in serious damage to hotels' and restaurants' revenue and brand image. For competitors who are plagued by fraudulent negative reviews and ratings, positively disconfirmed consumers tend to be more willing to post online reviews with ratings that exceed their own experiences, which can correct for unfairly diminished review ratings in the long term.

2.7.3 Limitations and Future Research Directions

This study is subject to a few limitations that can be addressed through future work. First, by using an experimental design, the study tested social influence effects (i.e., disconfirmation between post- consumption evaluation and prior review rating of the same product) on consumers' willingness to post online reviews and their online review rating decisions in the context of a hotel and restaurant. Future studies can examine social influence effects on consumers' online review behavior by using other outcome variables to provide additional implications for practice. For example, a possible research direction would be to apply text mining techniques to analyze the disconfirmation effect on the characteristics of online review textual content (e.g., review sentiment, review length, and words related to cognitive effort). Second, this study only tested the mediating effect of the eWOM motivation of concern for others on disconfirmation effects. Subsequent research could empirically test the mediation effects of other eWOM motivations for posting online reviews, such as helping the company

(Hennig-Thurau, Walsh, & Walsh, 2003), consumers' need for uniqueness (Tian, Bearden, & Hunter, 2001), and self-enhancement (Wu et al., 2017). Third, the study scenarios did not disclose information about the hotel or restaurant. Future studies could investigate the moderating effect of the hotel or restaurant brand on the influence of disconfirmation on consumers' willingness to post online reviews and review rating decisions. Potentially, concern for others may only apply to brands with a poor reputation. When perceived quality deviates from other consumers' average review rating for a brand with a poor reputation (vs. a good reputation), a consumer may be likely to attribute the conflict to other consumers' inaccurate or biased ratings (or hotel/restaurant review manipulation) and exhibit stronger motivation of concern for subsequent consumers. Finally, this study only used hypothetical scenarios involving a hotel and restaurant. To generalize these findings, future research could test the results of this study in a real-world context by collecting online secondary data.

CHAPTER 3

WHEN ONE'S EXPERIENCE DEVIATES FROM OTHERS': EXPLORING THE DISCONFIRMATION EFFECT ON CONSUMERS' ONLINE REVIEW CONTENT

3.1 Introduction

Online consumer review systems include information such as review ratings, textual reviews, and occasionally business rankings (Gössling, Hall, & Andersson, 2018). Online consumer-generated review information is often considered a truthful and unbiased reflection of consumers' product or service experiences (Hu, Liu, & Sambamurthy, 2011). An increasing number of consumers have come to rely on online reviews when making purchase decisions, including vacation choices (Dellarocas, 2006; Hu, Liu, & Sambamurthy, 2011; Xiang & Gretzel, 2010). Extant literature suggests that online reviews can positively influence product sales and firms' financial performance. For example, Öğüt and Onur Taş (2012) found that a 1% increase in an online review rating can result in an over 2.5% increase in sales per hotel room. Yacouel and Fleischer (2012) noted that positive consumer reviews can offer a price premium for hotels listed with online travel agents (OTAs). However, previous literature provides a limited understanding of consumers' online review behavior and the factors behind it (Moe & Schweidel, 2012).

Previous literature on services marketing suggests that word-of-mouth (WOM) can set up and affect customer expectations (Zeithaml et al., 1993). Zeithaml et al. (1993) proposed a conceptual model of the determinants of customer expectations. In the stage of information collection, customers gather information of a product/service from different sources, including traditional WOM and electronic WOM (eWOM), to learn what to expect from the product/service. On this basis, eWOM, which is largely represented by online reviews, appears to be an antecedent of customer expectations; positive eWOM increases consumer expectations, whereas negative eWOM decreases them (Ho, Wu, & Tan, 2017; Mauri & Minazzi, 2013). In particular, Mauri and Minazzi (2013) found that before deciding to book a hotel, consumers often search online and offline for hotel-related information to discover what to expect during their stay. Therefore, online reviews could shape consumers' pre-purchase expectations of a product/service when they check reviews posted online prior to making a final purchase decision. Upon purchase and consumption, the consumer forms a post-consumption evaluation of the specific product/service while also encountering a certain degree of disconfirmation when comparing his/her pre-purchase expectations and post-consumption evaluation of a product/service (Ho, Wu, & Tan, 2017). Given this disconfirmation, the consumer then faces the decision of what to write in a corresponding review. According to Anderson and Sullivan (1993), positive disconfirmation can increase customer satisfaction, whereas negative disconfirmation reduces it.

Prior work has studied the impact of disconfirmation on consumers' propensity to post online reviews as well as their review rating behavior (Ho, Wu, & Tan, 2017). However, such findings were based on secondary data from an e-commerce website selling manufacturing products; few studies have investigated the factors influencing a consumer's online review content, especially in terms of the social influence of prior reviews posted by other consumers. It is especially important to further test the influence of disconfirmation for experience-oriented hospitality products. To address these research gaps, the present study explores the following two research questions: (1) How does disconfirmation affect a consumer's online review content? and (2) Is there an asymmetrical effect on the influences of positive and negative disconfirmation on review content characteristics? By answering these questions, this research contributes to two literature streams—research on the social influence effects of consumer online reviews, and research regarding the relationship between disconfirmation and consumer post-consumption behavior—by extending the influence of disconfirmation from an offline context to an online context.

3.2 Literature Review

3.2.1 Consumer Disconfirmation and Online Reviewing Behavior

At the individual level, the process of consumer disconfirmation and online review behavior proceeds as follows. An individual consumer generally undertakes the following four steps during the purchasing-rating process (Figure 3.1). Step 1: to reduce uncertainty about product quality before purchasing a product/service, a consumer may check online reviews about that item, thus establishing pre-purchase expectations. Step 2: the consumer purchases and consumes the product/service. Step 3: the consumer forms a post-consumption evaluation and encounters a certain degree of disconfirmation upon comparing his/her pre-purchase expectations (informed by reviews posted by other consumers) and personal consumption experience. Step 4: given this disconfirmation, the consumer must decide whether to review the product/service. If the consumer decides to draft a review, he/she must decide what to write.

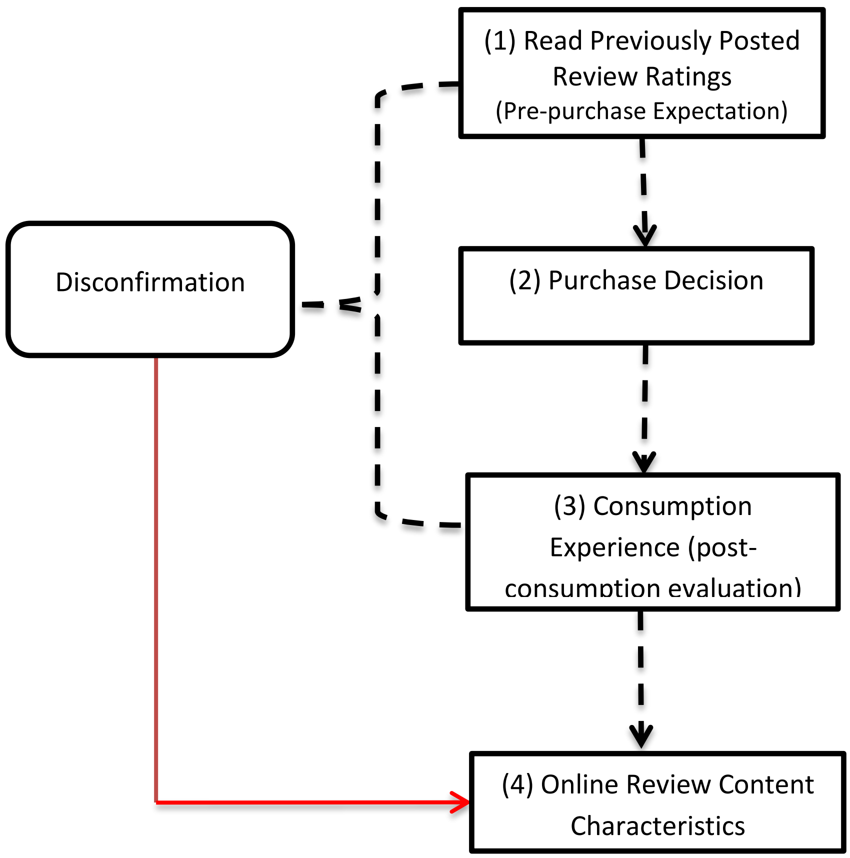

Figure 3.1 Process of Disconfirmation and Online Reviewing Behavior (Pre-purchase Review Exposure)

Occasionally, a consumer may acquire a product/service directly without checking online product reviews prior to making the purchase. In this case, the consumer may later see prior reviews and encounter a certain degree of disconfirmation when he/she decides to post an online review by visiting the online review webpage (Figure 3.2). The purchasing-rating process therefore changes accordingly. Step 1: the consumer purchases the product/service. Step 2: he/she forms a post-consumption evaluation. Step 3: the consumer faces the decision of whether to write an online review for the product/service. Step 4: if the consumer decides to write an online review, he/she visits the online review page and can see prior reviews of the same product/service posted by past consumers; exposure to prior reviews increases the probability that the consumer will experience disconfirmation. Step 5: given this disconfirmation, the consumer must decide what to include in the review. Regardless of whether consumers check prior reviews before or after consumption (or both), individuals will likely be socially influenced by prior reviews when providing their own product review and rating.

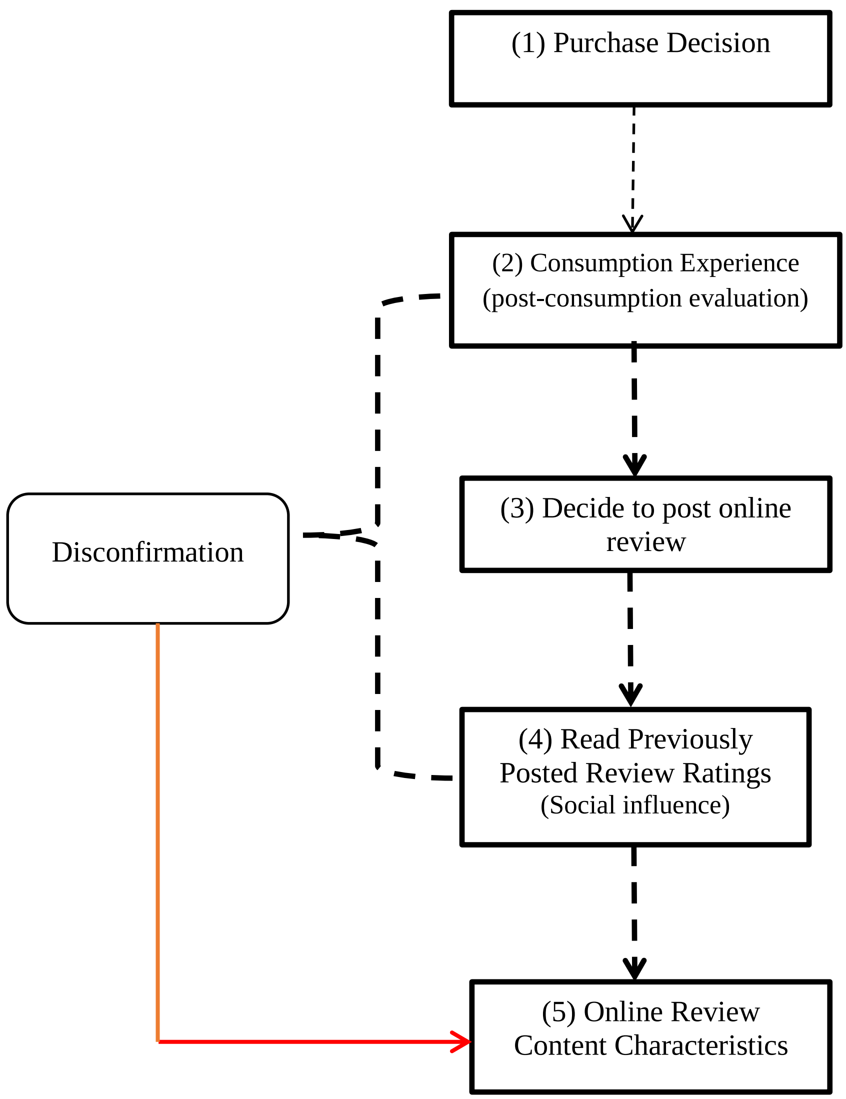

Figure 3.2 Process of Disconfirmation and Online Reviewing Behavior (Post-consumption Review Exposure)

3.2.2 Effects of Disconfirmation on Review Sentiment

Researchers have explained customer satisfaction using expectancy-disconfirmation theory (Oliver, 1981), one of the most widely accepted frameworks (Liu & Jang, 2009). Substantial research has empirically tested this theory in different fields and determined that customer satisfaction/dissatisfaction is derived from the comparison between customer expectations and perceived performance (Woodruff, Cadotte, & Jenkins, 1983). If the perceived performance meets expectations, then consumers' expectations are confirmed; if the performance exceeds expectations, then consumers experience a positive expectation; if performance fails to meet expectations, then consumers are faced with disconfirmation.

Disconfirmation leads to the formation of consumption emotions (Westbrook, 1987), with subsequent emotional reactions deemed either satisfaction or dissatisfaction (Woodruff, Cadotte, & Jenkins, 1983). Oliver (1993) stated that satisfaction/dissatisfaction is a combination of cognition and emotion; that is, satisfaction can be divided into two components: (1) cognitive beliefs about product/consumption outcomes; and (2) affective responses to the outcome. Westbrook (1987) pointed out that the frequency of positive product/consumption affect is related to judgments around product satisfaction. Furthermore, Oliver (1993) argued that positive consumption emotions are caused by a preliminary judgment of satisfaction with a service/product. When satisfied, a consumer will express positive consumption emotions; when dissatisfied, he/she will express negative consumption emotions.

In most cases, positive emotions about consumption (e.g., delight, contentment, and pleasure) result from positive disconfirmations, whereas negative emotions (e.g., disappointment, anger, and frustration) accompany negative disconfirmations (Woodruff, Cadotte, & Jenkins, 1983). Westbrook and Oliver (1991) stated that disconfirmation is positively associated with the pleasant surprise dimension of emotion and negatively associated with the hostility dimension. Similarly, Oliver, Rust, and Varki (1997) addressed that positive emotion is determined by how much the consumption experience exceeds one's expectations and how surprising the experience is. On the contrary, confirmation is much less likely to lead to more than a neutral, or at best weak, emotional response. Based on these findings, the following hypothesis is proposed:

Hypothesis 1 (H1): *Disconfirmation leads consumers to write reviews containing stronger sentiment (either positive or negative).*

3.2.3 Effects of Disconfirmation on Review Length and Review Text Characteristics

Social influence theory (Deutsch & Gerard, 1955; Fromkin, 1970; Sherif, 1936) suggests that people simultaneously experience a conformity motivation and "being different" motivation. Similarly, Dichter (1966) and Ho and Dempsey (2010) stated that an important driver behind individuals' WOM behavior is self-expression and the need to be different. According to Snyder and Fromkin (1980), this motivation of uniqueness becomes dominant when individuals perceive themselves as overly similar to others in a social group. For instance, Duval (1976) discovered that group members tend to contribute less to a specific task if they perceive other members to be highly similar to themselves. As such, it is reasonable to assume a consumer may contribute less to a review task (or even refuse to write a review altogether) when the product/consumption experience matches his/her expectations or would otherwise be similar to consumers' online review ratings. However, consumers tend to show strong normative conflicts if they perceive a high level of deviance from other group members or the social group norm, particularly when they believe other group members' opinions are incorrect or harmful (Ashforth, Kreiner, & Fugate, 2000; Hornsey, Oppes, & Svensson, 2002; Sridhar & Srinivasan, 2012). These dissenters can alienate themselves from the group norm and may attempt to persuade others to change their own behavior (Packer, 2008). Therefore, dissenting behaviors induced by normative conflict are prominent when people have the opportunity to make their behaviors highly visible and explain why they have deviated from the group norm or from other group members (Packer, 2008).

On a similar note, based on expectation-disconfirmation theory, Santos and Boote (2003) reported that indifference between predicted expectations and perceived product performance may lead to no affective action on the consumer's part. However, if a product's performance is better than predicted or even desired, then the consumer will feel satisfied and delighted (i.e., positive disconfirmation). In this case, the consumer is likely to compliment the target company on the given product/service. The intensity of the compliment will also increase in line with the degree of positive disconfirmation. In contrast, if negative disconfirmation occurs (i.e., perceived product performance is under a consumer's expectations), he/she will feel dissatisfied and sad, angry, or anxious; thus, the consumer will be more likely to complain to the target company. The intensity of the complaint increases with an increase in negative disconfirmation. According to cognitive dissonance theory (Festinger, 1957), disconfirmed expectations cause psychological discomfort (i.e., dissonance), leading to consumer complaints. Extending Oliver's (1980) study, Bearden and Teel (1983) incorporated consumer complaint behavior into the expectancy-disconfirmation model as a post-satisfaction behavior and found expectation and disconfirmation to be positively related to satisfaction, which negatively influences subsequent complaints. Cho, Im, Hiltz, and Fjermestad (2002) also revealed that unmet consumer expectations are the primary drivers behind consumers' online and offline complaint behavior.

According to the psychological literature, people tend to understand their past experiences to better prepare for the future (Park, 2010; Pennebaker, 1997), especially when they encounter unexpected, emotional, or negative experiences (Wilson & Gilbert, 2008; Wong & Weiner, 1981). These efforts involve several cognitive processes, among which analytical writing (Lyubomirsky, Sousa, & Dickerhoof, 2006) and explaining (Malle, 2004) are common. A cognitive process can help people come to an understanding of their overall experience and assess the causes and outcomes of this experience (Wilson & Gilbert, 2008). Accordingly, the following hypotheses are proposed:

Hypothesis 2 (H2): *Disconfirmation leads consumers to write longer reviews.*

Hypothesis 3 (H2): *Disconfirmation leads to more language reflecting causal-explanation processes in online review text.*

3.2.4 Asymmetrical Effects of Disconfirmation

Prospect theory (Kahneman & Tversky, 1979) proposed a utility function which is S-shaped, and is normally steeper for losses than for gains. Therefore, people tend to be loss aversive and exhibit negativity bias, as negative information is usually perceived as more informative and diagnostic than positive or neutral information (Herr, Kardes, & Kim, 1991; Kahneman & Tversky, 1979). For example, Mittal, Ross, and Baldasare (1998) found positive performance of an attribute to exert a smaller influence on customer satisfaction and repurchase intention compared to negative performance of the same attribute.

In principle, the expectancy-disconfirmation model is similar to prospect theory in two respects (Palit, 1999; Yi & La, 2003). First, both models have a reference point that bisects gains and losses. Prospect theory's reference point corresponds to the point at which perceived product performance equals the expectation in the expectancy-disconfirmation model. Gains and losses in prospect theory correspond to positive and negative disconfirmation, respectively, in the expectancy-disconfirmation model. Second, the *y*-axis refers to utility in prospect theory and consumer satisfaction in the expectancy-disconfirmation model. Furthermore, Anderson and Sullivan (1993) and Palit (1999) each found that consumers tend to weigh negative disconfirmation more heavily than positive disconfirmation. They also proposed an asymmetrical loss function, shaped similarly to the S-shaped utility function, to elucidate the relationship between disconfirmation and consumer satisfaction. Based on survey data from various products in Sweden, Anderson and Sullivan (1993) determined that disconfirmation has a significant effect on satisfaction and repeat purchase intention, with negative disconfirmation demonstrating a stronger effect than positive disconfirmation. Palit (1999) measured the level of consumer satisfaction in cases of negative and positive disconfirmation and reported that consumers exhibit strong loss aversion when evaluating satisfaction. In the hospitality industry, Yi and La (2003) surveyed 256 Korean restaurant patrons and found that positive and negative disconfirmations have an asymmetrical influence on customer satisfaction, with the latter showing a greater effect. They further stated that asymmetrical influence becomes prominent when consumers have high and affirmative confidence in their expectations. Previous studies also revealed an asymmetrical effect of disconfirmation on consumer post-consumption WOM behavior, with negative disconfirmation exhibiting a larger effect than positive disconfirmation (Anderson & Sullivan, 1993). Therefore, it is reasonable to examine whether customers respond asymmetrically when writing review content as well, hence the following hypotheses:

Hypothesis 4a (H4a): *Negative disconfirmation has a stronger effect than positive disconfirmation on review sentiment.*

Hypothesis 4b (H4b): *Negative disconfirmation has a stronger effect than positive disconfirmation on review length.*

Hypothesis 4c (H4c): *Negative disconfirmation has a stronger effect than positive disconfirmation on review causal-explanation content.*

The research framework of this study (Figure 3.3) was developed based on the preceding literature review.

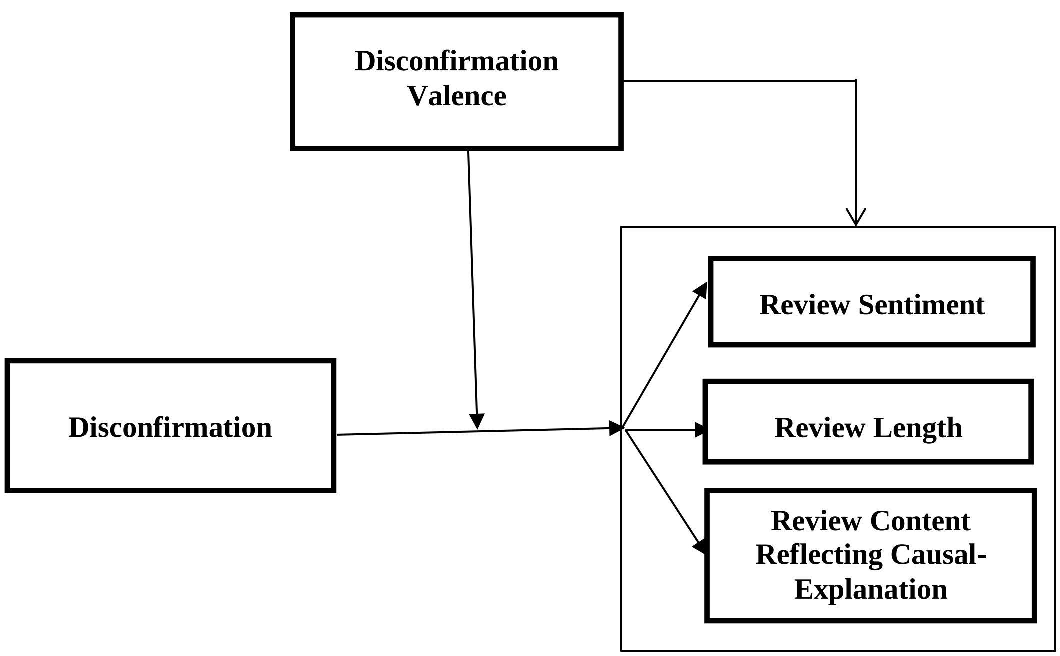

Figure 3.3 Research Framework

3.3 Methodology

3.3.1 Sample

Study data were collected from a popular online review website, Yelp.com (Li et al., 2017). The dataset consisted of online reviews of restaurants, which comprise most reviews on Yelp (Yelp, 2011). The most popular 300 restaurants in Las Vegas were selected based on the number of online reviews to ensure a sufficient number of reviews per restaurant. The establishments ranged from casual to fine dining, limited service to full service, and included all restaurant categories (e.g., American, Mexico, Italian). The total sample consisted of 186,714 reviews. Similar to Hong et al. (2016), a randomly selected set of 150 reviews was verified to ensure review accuracy.

The data panel included three different categories: reviews, reviewers, and restaurants. Data on the review author, numerical rating on a 5-star scale, time stamp, review text, and usefulness votes were collected for each review. All restaurant reviews were arranged by restaurant in chronological order. Each reviewer's website registration date and yearly online status (elite or non-elite) were collected along with information on each restaurant's category and price range.

3.3.2 Variables Operation and Summary Statistics

Rating disconfirmation ($Disconfirmation_{ijt}$). Following Hong et al. (2016) and Yin, Mitra, and Zhang (2016), rating disconfirmation was measured as the difference between the rating of a focal review and the prior average rating before the review for a specific restaurant. The average review rating for the restaurant posted prior to that of the focal review (i.e., the *n*th review) was used to measure pre-purchase expectations (Hong et al., 2016; Sridhar & Srinivasan, 2012), namely the average rating of the first, second,

…, $(n-1)$th review ratings for restaurant j ($AveOthers_{jt}$). Rather than using the exact average rating of a restaurant, the rounded average review rating to the nearest half-star was used in this study as publicized by Yelp (Ma et al., 2013). This rounded average rating is consistent with that displayed on Yelp. $absDisconfirmation_{ijt}$ represents the absolute value of $Disconfirmation_{ijt}$.

Review sentiment ($Sentiment_{ijt}$). The sentiment of each review was calculated by using the Naïve Bayes classifier, a well recognized classifier in the categorization of text (McCallum & Nigam, 1998). The study attempts to determine the sentiment of restaurant textual reviews based on a training set. Sentiment values range from 0–1; the larger the sentiment value, the more positively oriented the textual review. By contrast, the smaller the sentiment value, the more negatively oriented the review. The average accuracy of the naïve Bayes classifier was 79%; recall of positive and negative reviews was 78% and 80%, respectively; and the precision of positive and negative reviews was 80% and 79%, respectively. A support vector machine classifier was also constructed, but its performance was not as good as that of the naïve Bayes classifier. Therefore, the naïve Bayes algorithm was employed to calculate review sentiment.

Review length ($Length_{ijt}$). The total number of words in a review was used to measure review length, by applying the latest version of the Linguistic Inquiry and Word Count (LIWC) text mining program (Pennebaker, Booth, & Francis, 2007).

Review content reflecting a causal-explanation process ($Explain_{ijt}$). LIWC was also used to analyze the percentage of causal-explanation words (e.g., *cause, reason, because, thus, infer, hence, effect, responsible*) in each review (Pennebaker, Booth, & Francis, 2007). LIWC calculates the percentage of words matched to pre-defined dictionaries in a text (Pennebaker, Booth, & Francis, 2007). A higher percentage of causal-explanation words in the review text indicated the consumer was more thoughtful regarding the causes and reasons of a consumption experience (Brett et al., 2007). In addition to its frequent use in psychology, the LIWC program has become increasingly common in marketing studies (Ludwig et al., 2013; Sridhar & Srinivasan, 2012) and information systems research (Goes, Lin, & Au Yeung, 2014; Hong et al., 2016; Yin, Bond, & Zhang, 2014).

Table 3.1 Control Variables

Variables	**Description**
(1) Consumer expectations	
Prior average review rating ($AveOthers_{jt}$)	Average rating prior to the current review for a specific restaurant
(2) Consumer heterogeneity	
Consumer tenure ($Tenure_{it}$)	The number of months since the consumer registered on Yelp
Consumer online status ($Status_{it}$)	Whether the reviewer was labeled “Elite” in the year when the review was posted (0 = no; 1 = yes)
(3) Restaurant heterogeneity	
Restaurant popularity ($Popularity_{jt}$)	Number of review ratings for restaurant j at time t (prior to the current review)
Restaurant price range ($Price_j$)	A categorical variable classifying restaurants by price range (1 = inexpensive; 2 = moderate; 3 = pricey; 4 = ultra high-end)
Restaurant category ($Category_j$)	A categorical variable that divides restaurants into a variety of categories
(4) Time heterogeneity	
Year timing effect ($Year_{ijt}$)	Year in which review was written (reference year = 2005)
Month timing effect ($Month_{ijt}$)	Month in which review was written (reference month = January)

Table 3.2 Variable Descriptions

Variable	Mean	Std. Dev.	Min	Max
Dependent variables				
Sentiment	.7859274	.3507303	0	1
Length	134.2243	120.8954	1	1015
Explain	.86085	1.136471	0	33.33
Independent variables				
Disconfirmation	-.0355922	1.131003	-4	3.5
absDisconfirmation	.869699	.7239166	0	4
Control variables				
AveOthers	3.882435	.4733675	1.5	5
Tenure	22.81882	19.61112	0	117
Status	--	--	0	1
Popularity	526.5275	614.0053	0	4136
Price	--	--	1	4
Category	--	--	1	178
Year	--	--	2004	2015
Month	--	--	1	12

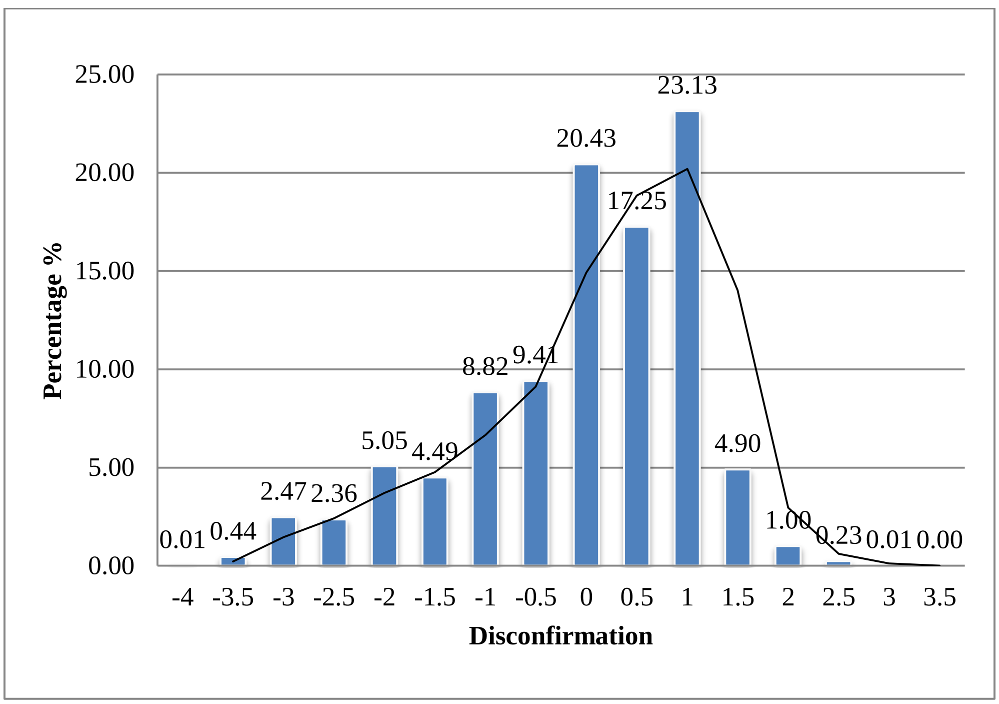

Figure 3.4 Disconfirmation Distribution

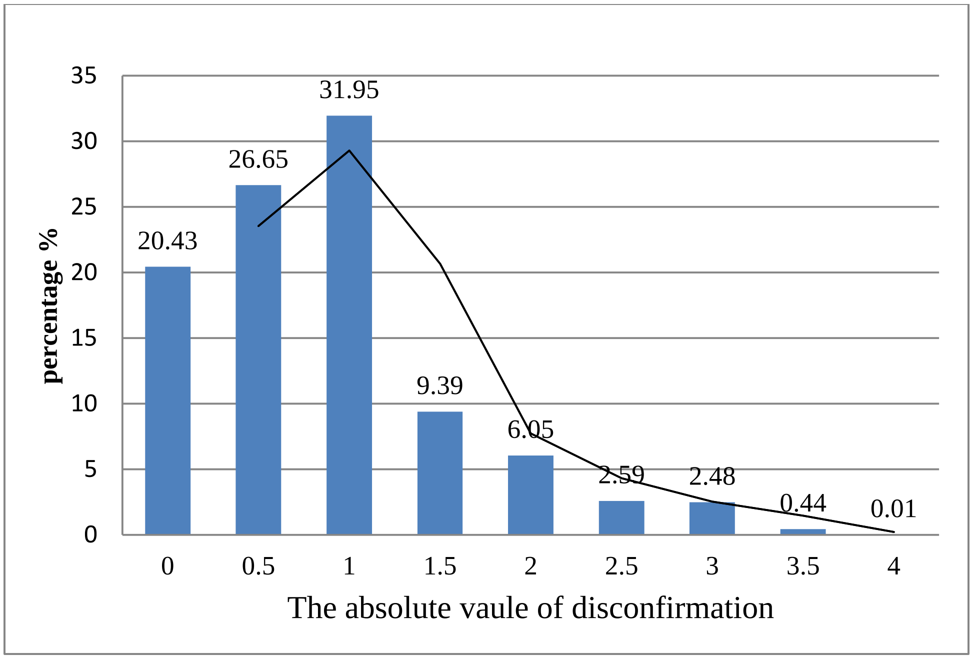

Figure 3.5 Absolute Value of Disconfirmation Distribution

Control variables. The author controlled for the average review rating prior to publication of the focal review as a proxy for consumer expectations of the restaurant. According to expectancy-disconfirmation theory (e.g., Oliver, 1980), expectation and disconfirmation can each affect consumer satisfaction along with online review behavior. The author also controlled for consumer tenure and consumer online status; consumers' review-writing styles could evolve as they accumulate review experience or become affiliated with different online statuses (Huang et al., 2016). To account for unobserved restaurant heterogeneity, restaurant popularity was also controlled, measured by the number of reviews for restaurant j at time t (prior to the current review). Moreover, two variables were included in the model to control for unobserved restaurant heterogeneity, which does not vary over time: the price range of the restaurant (to account for customers' price sensitivity), with price level used as a proxy for average perceived food quality; and the restaurant category (e.g., American, Mexican, Chinese), as consumers' cuisine preferences may affect their written reviews and perceptions of review helpfulness. To account for unobserved time heterogeneity, both models included a series of dummy variables reflecting the year or month when the review was posted and available on Yelp. Reviews written in different years or months could be different due to unobserved trends, shocks, or seasonal effects. All control variables and their descriptions are summarized in Table 3.1.

Table 3.2 presents the summary statistics for the variables, and Figures 3.4–3.5 show the distribution of key variables (i.e., rating disconfirmation and its absolute value). The two figures indicate that 20.43% of consumers provided exactly the same evaluation as the prior average review rating. In fact, the majority of consumers (31.95%) demonstrated disconfirmations equal to 1, followed by 26.65% of consumers who exhibited disconfirmations equal to 0.5; 15.44% of consumers submitted reviews with disconfirmations of 1.5 or 2, and only 5.52% of consumers expressed distinctly different opinions from prior consumers (i.e., disconfirmation values greater than 2).

3.3.3 Econometric Specifications

This study estimated a series of alternative models to demonstrate the robustness of the findings. In some models, restaurant or consumer static characteristics were not included when restaurant or consumer fixed effects were incorporated into the model. The author examined disconfirmation influence by using ordinary least squares regression with one-way fixed effects (time fixed effects), two-way fixed effects (time and business/consumer fixed effects), and three-way fixed effects (time, business, and consumer fixed effects). In the dataset, unobserved heterogeneity possibly occurred at the time level, restaurant level, and consumer level; therefore, the identification strategy relied on the application of three-way fixed effects (i.e., the model incorporating time, restaurant, and consumer fixed effects), which was the most conservative estimation (Huang et al., 2016). In line with Cornelissen (2008), the following three-way fixed effects econometric models were established:

$$Sentiment_{ijt} = \alpha_1 Disconfirmation_{ijt} + \sum\nolimits_I \rho_i * C_i + \sum\nolimits_J \lambda_j * R_j + \sum\nolimits_T \tau_t * M_t + Control_{ijt} + \varepsilon_{ijt} \quad (1)$$

$$Length_{ijt} = \beta_1 absDisconfirmation_{ijt} + \sum\nolimits_I \rho_i * C_i + \sum\nolimits_J \lambda_j * R_j + \sum\nolimits_T \tau_t * M_t + Control_{ijt} + \varepsilon_{ijt} \quad (2)$$

$$Explain_{ijt} = \gamma_1 absDisconfirmation_{ijt} + \sum\nolimits_I \rho_i * C_i + \sum\nolimits_J \lambda_j * R_j + \sum\nolimits_T \tau_t * M_t + Control_{ijt} + \varepsilon_{ijt} \quad (3)$$

where subscript i represents consumers, j represents restaurants, and t represents time; C_i refers to consumer fixed effects; R_j refers to restaurant fixed effects; M_t refers to month and year fixed effects; and $Control_{ijt}$ refers to the control variables introduced above.

3.4 Results

3.4.1 Disconfirmation Effect on Consumers' Online Review Content

To demonstrate the robustness of the estimation results, one-way, two-way, and three-way fixed effects were estimated. Tables 3.3–3.5 present the estimation results. Models 1.1, 2.1, and 3.1 included one-way fixed effects, which only controlled for time (year and month) fixed effects. Models 1.2, 2.2, and 3.2 included two-way fixed effects, controlling for time and restaurant fixed effects. Models 1.3, 2.3, and 3.3 also included two-way fixed effects, controlling for time and consumer fixed effects. Models 1.4, 2.4, and 3.4 contained three-way fixed effects, controlling for time, restaurant, and consumer fixed effects. The identification strategy in this study relied on the application of three-way fixed effects.

Table 3.3 displays the estimation results of the disconfirmation effect on review sentiment. Results were quite robust across Models 1.1–1.4. The results of Model 1.4 show that rating disconfirmation had a significantly positive effect on review sentiment (coefficient = 0.1651363, $p < 0.01$), suggesting that a consumer whose product evaluation disconfirmed that of prior reviewers was more likely than others to write a sentimental review; therefore, Hypothesis 1 (disconfirmation leads consumers to write reviews with stronger sentiment) was supported.

Table 3.4 shows the estimation results of the disconfirmation effect on review length. The estimation results were highly stable across Models 2.1–2.4. Model 2.4 indicated that consumer rating disconfirmation (i.e., the absolute value) had a significantly positive effect on review length (coefficient = 15.3416, $p < .01$); as such, Hypothesis 2 (disconfirmation leads consumers to write longer reviews) was supported.

Table 3.5 presents the estimation results of the disconfirmation effect on review content reflecting a causal-explanation process. According to Model 3.4, consumer rating disconfirmation (i.e., the absolute value) exerted a significant and positive influence on review content reflecting a causal-explanation process (coefficient = 0.0462842, $p < 0.01$). That is, a consumer whose product evaluation disconfirmed that of others tended to explain why he/she expressed a different opinion compared to other reviewers in the body of his/her online review. Hypothesis 3 (disconfirmation leads to more language reflecting causal-explanation processes in online review text) was thus supported.

Table 3.3 Empirical Results—Review Sentiment

	Model 1.1 OLS	Model 1.2 Restaurant FE	Model 1.3 Consumer FE	Model 1.4 Three-way FE
Constant	.0331021 (.0431084)	.0317615 (.0457313)	.1346706*** (.0439244)	.1294639*** (.0503069)
Disconfirmation	**.1746228*** (.0006549)**	**.1746839*** (.0006571)**	**.1640013*** (.0011805)**	**.1641413*** (.0011866)**
AveOthers	.1665965*** (.0023929)	.1733901*** (.00422)	.159285*** (.0038969)	.1651363*** (.0066485)
Tenure	8.99e-06 (.0000372)	.0000106 (.0000372)	.0000474 (.0007172)	.0000187 (.0007068)
Status	.0448506*** (.0016514)	.0445471*** (.0016493)	.0150154** (.0062195)	.0150086** (.0062083)
Popularity	7.03e-06*** (1.87e-06)	7.23e-06*** (2.29e-06)	1.93e-06 (3.14e-06)	3.44e-06 (3.86e-06)
Price				
Price = 2	.030753*** (.0049614)	--	.0314524*** (.0081058)	--
Price = 3	.0545764*** (.0058215)	--	.0510976*** (.0094225)	--
Price = 4	.0434824*** (.0065888)	--	.03157*** (.0108735)	--
Category (*n* = 178)	Yes	No	Yes	No
Year	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Restaurant fixed effects	**No**	**Yes**	**No**	**Yes**
Consumer fixed effects	No	No	Yes (82,970 categories)	Yes
Observations	183,642	18,3642	183,642	183,642
R^2	0.3668	0.3703	0.6668	0.6688
Adj R^2	0.3661	0.3692	0.3909	0.3938

Note: Values in parentheses indicate the *z* ratio. Asterisks indicate that the coefficient is significant at the *10%, **5%, and ***1% level.

Table 3.4 Empirical Results—Review Length

	Model 2.1 OLS	Model 2.2 Restaurant FE	Model 2.3 Consumer FE	Model 2.4 Three-way FE
Constant	-72.09731*** (11.26554)	-11.59555*** (12.93901)	-27.62754 (23.60515)	20.57035 (25.40527)
absDisconfirmation	**12.32379*** (.4113696)**	**12.24817*** (.4102574)**	**15.37097*** (.5890083)**	**15.3416*** (.5852484)**
AveOthers	14.03136*** (.9571061)	5.277315*** (1.762933)	15.22878*** (1.265267)	9.165296*** (2.241014)
Tenure	.3164323*** (.0147968)	.3107841*** (.014741)	1.40756*** (.4318645)	1.378498*** (.4400381)
Status	73.74174*** (.7339155)	74.15342*** (.7301317)	24.97086*** (2.328825)	25.31793*** (2.30187)
Popularity	-.0067296*** (.0007062)	-.0076768*** (.0009005)	-.0080841*** (.0009667)	-.0091477*** (.0012113)
Price				
Price = 2	13.59536*** (1.693269)	--	23.86207*** (2.297063)	--
Price = 3	32.56555*** (2.143013)	--	49.52805*** (2.87187)	--
Price = 4	48.59377*** (2.963264)	--	69.12654*** (3.958917)	--
Category (*n* = 178)	Yes	No	Yes	No
Year	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Restaurant fixed effects	**No**	**Yes**	**No**	**Yes**
Consumer fixed effects	No	No	Yes (82970 categories)	Yes
Observations	186,256	186,256	186,256	186,256
R^2	0.1244	0.1349	0.7172	0.7230
Adj R^2	0.1235	0.1334	0.4842	0.4943

Note: Values in parentheses indicate the *z* ratio. Asterisks indicate that the coefficient is significant at the *10%, **5%, and ***1% level.

Table 3.5 Empirical Results—Review Cause

	Model 3.1 OLS	Model 3.2 Restaurant FE	Model 3.3 Consumer FE	Model 3.4 Three-way FE
Constant	.6665916*** (.2243768)	.7010717*** (.23225)	.7395154*** (.1997656)	.9575702*** (.2158299)
absDisconfirmation	**.0525958*** (.0038112)**	**.0529222*** (.0038213)**	**.0456198*** (.0062865)**	**.0462842*** (.0063031)**
AveOthers	.0036575 (.0088183)	-.0191725 (.0160875)	-.0097664 (.0135136)	-.0344133 (.0230243)
Tenure	.0008808*** (.0001498)	.0009052*** (.00015)	.0007794 (.0034974)	.0005233 (.0032941)
Status	.0738899*** (.0056954)	.0752935*** (.0057025)	.0217369 (.0204325)	.0231427 (.0204139)
Popularity	3.45e-07 (7.64e-06)	-.0000103 (9.54e-06)	.0000193 (.0000119)	.0000121 (.0000147)
Price				
Price = 2	-.0609439*** (.021833)	--	-.00554 (.0322191)	--
Price = 3	-.1172276*** (.0247846)	--	-.0507045 (.0371124)	--
Price = 4	-.0948061*** (.0278034)	--	-.0364406 (.0426199)	--
Category (*n* = 178)	Yes	No	Yes	No
Year	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Restaurant fixed effects	**No**	**Yes**	**No**	**Yes**
Consumer fixed effects	No	No	Yes (82970 categories)	Yes
Observations	186,256	186,256	186,256	186,256
R^2	0.0076	0.0098	0.5209	0.5223
Adj R^2	0.0065	0.0081	0.1262	0.1277

Note: Values in parentheses indicate the *z* ratio. Asterisks indicate that the coefficient is significant at the *10%, **5%, and ***1% level.

3.4.2 Asymmetrical Effects of Positive vs. Negative Disconfirmation

To investigate the asymmetrical effects of positive and negative disconfirmation, consumer online reviews were divided into two groups. If the rating of a specific review was lower than the prior average review rating for the associated restaurant, the review was included in the negative disconfirmation group; if the rating of a specific review was higher than the prior average review rating for the associated restaurant, the review was categorized into the positive disconfirmation group. In total, 85,415 reviews comprised the positive disconfirmation group, and 60,762 comprised the negative disconfirmation group. The author then ran the three-way fixed effects model using the positive and negative disconfirmation groups, respectively. Estimation results appear in Table 3.6, indicating that negative disconfirmation exerted a stronger effect than positive disconfirmation; that is, consumers reacted more powerfully to negative disconfirmation than to positive disconfirmation in terms of review sentiment, review length, and review content reflecting causal-explanation processes. Hypotheses 4a, 4b, and 4c (the effects of positive and negative disconfirmation on review sentiment, review length, and review causal-explanation content, respectively, are asymmetrical) were therefore supported.

3.4.3 Additional Analysis—Effects of Disconfirmation and Online Review Content Characteristics on Perceived Review Helpfulness

In subsequent analysis, this study investigated the mechanism behind whether and how disconfirmation influenced perceived review helpfulness. According to previous literature (Hong, Chen, & Hitt, 2014; Sun, 2012), to reduce risk and assess whether a product suits their tastes, consumers generally seek out different opinions of a product before deciding to purchase. Reviews with ratings that deviate from the prior average review rating are more likely to stand out, as they provide unique information as an

Table 3.6 Empirical Results— Asymmetrical Effects of Positive vs. Negative Disconfirmation

	Review Sentiment		Review Length		Review Cause	
	Model 1.5 Positive	Model 1.6 Negative	Model 2.5 Positive	Model 2.6 Negative	Model 3.5 Positive	Model 3.6 Negative
Constant	.6317403*** (.0577588)	-.0618342 (.1100808)	63.69956*** (23.83975)	45.87949 (34.60009)	1.0458*** (.3284483)	1.082101*** (.3402489)
Disconfirmation (or absDisconfirmation)	**.0616224*** (.0054073)**	**.2304171*** (.0049205)**	**8.830415*** (2.102437)**	**19.63404*** (1.527834)**	**-.0039181 (.0268299)**	**.0703878*** (.014713)**
AveOthers	.0647056*** (.0105214)	.2252112*** (.0186346)	6.667382 (4.431203)	6.630488 (5.742265)	-.04044 (.0495308)	-.0829397 (.0508636)
Tenure	-.0003891 (.0005471)	-.0001047 (.0008)	.562074** (.2271732)	1.550355*** (.2381678)	.0009483 (.0030714)	.001646 (.0021412)
Status	.0134495 (.0087751)	-.0027246 (.018112)	26.26294*** (4.53022)	21.34885*** (5.488248)	.0482407 (.0393833)	.0219578 (.0448516)
Popularity	-5.48e-06 (5.88e-06)	.0000117 (.0000122)	-.004458* (.0024766)	-.0145746*** (.0034519)	-.0000109 (.0000298)	-.0000317 (.0000369)
Price	--	--	--	--	--	--
Category (*n* = 178)	No	No	No	No	No	No
Year	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes
Restaurant FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Consumer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85,415	60,762	86,646	61,561	86,646	61,561
R^2	0.6403	0.7598	0.8038	0.7897	0.6721	0.6806
Adj R^2	0.0710	0.3579	0.4946	0.4395	0.1554	0.1485

Note: Values in parentheses indicate the *z* ratio. Asterisks indicate that the coefficient is significant at the *10%, **5%, and ***1% level.

alternative viewpoint (Cao, Duan, & Gan, 2011).

In addition to the influence of review rating disconfirmation, review text characteristics can also influence the perceived helpfulness of a review. First, a consumer's sentiment could be effectively communicated via the review text and may effectively influence readers' perceptions (Harris & Paradice, 2007; Walther & D'Addario, 2001). Salehan and Kim (2016) found that in addition to the numerical rating, the sentiment exhibited in review text affects perceived review helpfulness; compared with less-sentimental reviews, highly sentimental reviews are perceived as more accurate representations of a consumer's product experience. Second, compared to briefer reviews, longer reviews tend to contain more information (Pan & Zhang, 2011) regarding how and where a product was purchased and used (Mudambi & Schuff, 2010). In hospitality management, review length has been reported to exert a significantly positive influence on review helpfulness for restaurants (Liu & Park, 2015; Yang et al., 2017) and tourism attractions (Fang et al., 2016). Third, an explanation is essential for influencing readers, as information with no explanation is not sufficient to affect the attitude predictability and perceived helpfulness of a review (Moore, 2015). Moore (2015) and Wilson and Gilbert (2008) argued that explanatory language in online reviews indicates why the product was chosen, what specific usage/consumption experiences occurred, or why the product or experience was liked or disliked. This additional information can help other people predict with more confidence whether they would prefer the reviewed product (Tormala & Rucker, 2007). Relatedly, Ahluwalia and Gurhan-Canli (2000) contended that online reviews expressing a clear attitudinal direction towards the product by offering reasons are perceived as more useful. The author therefore tested the influences of review rating disconfirmation, review sentiment, review length, and review content reflecting causal-explanation processes on perceived review helpfulness. Similar to Li et al. (2017) and Chen and Lurie (2013), a negative binomial regression with robust standard errors was applied in this study, as the dependent variable is a count variable.

To test the robustness of the model, a series of alternative models were estimated. Model 4.1 only included control variables found to be important in previous research (i.e., review-, reviewer-, restaurant-, and time-level variables). Review-level control variables included review readability (*Readability*), measured by the Gunning-Fog Index readability index (Gunning, 1969) and the number of days for which the review was available on Yelp (*Date*). Reviewer-level control variables included the consumer's "Elite" status in the year when the review was written (1 = elite; 0 = non-elite), number of Yelp friends (*Friends*), and reviewer tenure (*Tenure*). Restaurant-level control variables included prior average review rating (*AveOthers*), restaurant popularity (*Popularity*), restaurant price range (*Price*), and restaurant category (*Category*). Time-level control variables included year fixed effects (*Year*) and month fixed effects (*Month*). Based on Model 4.1, Model 4.2 also incorporated the variables of interest, namely review rating disconfirmation, review sentiment, review length, and review content reflecting causal-explanation processes. Unlike Model 4.1, Model 4.3 replaced the restaurant-level control variables that did not vary with time, such as price and restaurant type, with restaurant fixed effects. Based on Model 4.3, Model 4.4 incorporated the variables of interest. Estimation results are shown in Table 3.7. The estimation results of Models 4.1–4.4 were quite robust. First, review rating disconfirmation was found to be positively associated with perceived review helpfulness, meaning that a disconfirmed review was likely to receive more review helpfulness votes. Second, a U-shaped relationship appeared between review sentiment and review helpfulness, indicating that sentimental reviews, whether positive or negative, were perceived as more helpful than neutral online reviews. Third, review length was positively associated with perceived review helpfulness, suggesting that compared to shorter online reviews, longer reviews were perceived as more helpful. Fourth, review language reflecting causal-explanation processes was also positively associated with review helpfulness; therefore, online reviews expressing a clear attitudinal direction towards a restaurant by explaining consumers' reasons were perceived as being more helpful than those without a clear attitudinal direction.

Previous research consistently found negative reviews to be perceived as more informative and helpful than positive reviews due to negativity bias (Chen & Lurie, 2013; Mudambi & Schuff, 2010). Therefore, it is reasonable to assume that compared with reviews with positive rating disconfirmations, those with negative rating disconfirmations will likely receive more helpfulness votes. The author thus estimated the asymmetrical effects between positive and negative disconfirmations. To test the robustness of the model, a series of alternative models were also estimated. Models 4.5 and 4.6 included restaurant-level control variables of price range and restaurant category, and Models 4.7 and 4.8 replaced these two variables with restaurant fixed effects. Estimation results are shown in Table 3.8. The results were quite robust across the four models and demonstrated a stronger effect of negative disconfirmation than positive disconfirmation. In other words, consumers tended to react more distinctly to negative disconfirmation than to positive disconfirmation in terms of perceived review helpfulness.

Table 3.7 Empirical Results—Effect of Disconfirmation on Review Helpfulness

	No Restaurant FE		Restaurant FE	
	Model 4.1	Model 4.2	Model 4.3	Model 4.4
Constant	-4.513658***	-5.413289***	-5.113468***	-5.945353***
	(1.556586)	(1.503733)	(1.549753)	(1.500158)
absDisconfirmation		**.1684691*** **		**.1693124*** **
		(.0054384)		**(.0054285)**
Sentiment^2		.6117797***		.6260365***
		(.0544765)		(.0543417)
Sentiment		-.7446413***		-.7547371***
		(.0594076)		(.0592457)
Length		.0029366***		.0028456***
		(.0000295)		(.0000294)
Explain		.0265874***		.0253282***
		(.0034736)		(.0034616)
Readability	.0178275***	.0019365*	.017266***	.0022266*
	(.0012215)	(.0011493)	(.0012063)	(.0011424)
Date	.0006762	.0009785**	.0008117*	.001053***
	(.0004184)	(.0004045)	(.0004157)	(.0004027)
Status	.7764913***	.6608259***	.7931238***	.6773583***
	(.0090057)	(.0087244)	(.0089308)	(.0086872)
Friends	.0035431***	.0029763***	.0035019***	.0029635***
	(.0000362)	(.0000313)	(.0000353)	(.0000308)
Tenure	.0049889***	.0045124***	.0050207***	.0045593***
	(.0002109)	(.0002041)	(.0002102)	(.0002038)
Hotelmean2	.164561***	.1652022***	.1271163***	.1319841***
	(.0123157)	(.0120073)	(.0211425)	(.0204987)
Popularity	-.0001461***	-.0001164***	-.0000772***	-.0000592***
	(.0000107)	(.0000104)	(.0000134)	(.000013)
Price				
Price = 2	-.0620617**	-.1390603***	--	--
	(.0281023)	(.0271045)		
Price = 3	.2394706***	.0898995***	--	--
	(.0324345)	(.0313102)		
Price = 4	.198097***	-.0191202	--	--
	(.0381345)	(.0370285)		
Category (*n* = 178)	Yes	Yes	No	No
Month	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Restaurant FE	**No**	**No**	**Yes**	**Yes**
Alpha	1.062118***	.8264936***	1.012833***	.7975874***
	(.009031)	(.0076732)	(.0087575)	(.0075011)
Likelihood-ratio	6.7e+04	5.3e+04	6.4e+04	5.1e+04
Test of alpha = 0	(P=0.000)	(P=0.000)	(P=0.000)	(P=0.000)
Log likelihood	-219303.14	-210482.07	-217919.18	-209480.83
LR χ^2	47366.84	61076.56	50134.76	63079.03
Pseudo R^2	0.0975	0.1267	0.1032	0.1309

Note: Values in parentheses indicate the *z* ratio. Asterisks indicate that the coefficient is significant at the *10%, **5%, and **1% level.

Table 3.8 Empirical Results—Asymmetrical Effects of Disconfirmation

	No Restaurant FE		Restaurant FE	
	Model 4.5 (Pos)	Model 4.6 (Neg)	Model 4.7 (Pos)	Model 4.8 (Neg)
Constant	-5.209374**	-3.706606	-5.492297**	-4.257973*
	(2.452108)	(2.497266)	(2.4509)	(2.479695)
absDisconfirmation	**.1379677*** **	**.2609909*** **	**.1284573*** **	**.2560037*** **
	(.0178667)	**(.0086275)**	**(.0186094)**	**(.008624)**
Sentiment^2	.5313932***	.5437272***	.5433189***	.5385771***
	(.1114007)	(.0775492)	(.1112407)	(.0769723)
Sentiment	-.6924819***	-.6134747***	-.6857109***	-.606233***
	(.1340446)	(.0801561)	(.1337855)	(.0795791)
Length	.0032192***	.002538***	.0031419***	.0024343***
	(.0000456)	(.0000465)	(.0000456)	(.0000461)
Cause	.0225209***	.0318695***	.0219215***	.0292102***
	(.0051325)	(.0058422)	(.0051214)	(.0057958)
Readability	.0035452**	-.0015347	.0032891*	-.0017827
	(.0017386)	(.0018944)	(.0017343)	(.0018715)
Date	.0004664	.0006216	.0005911	.0007318
	(.0006037)	(.0006743)	(.000602)	(.0006679)
Elite	.6656301***	.645177***	.6735196***	.6721025***
	(.013154)	(.0149749)	(.0131107)	(.0148172)
Friends	.0030498***	.0029046***	.0030282***	.002887***
	(.0000486)	(.0000535)	(.0000478)	(.0000517)
Tenure	.0048715***	.004371***	.0049246***	.0045152***
	(.0003065)	(.0003383)	(.0003066)	(.0003358)
AveOthers	.2806014***	-.0362662*	.1797878***	-.0623198*
	(.0197023)	(.0193502)	(.0343075)	(.0333033)
Popularity	-.0001027***	-.0001193***	-.0000518**	-.0000579***
	(.0000164)	(.0000171)	(.0000203)	(.0000219)
Price				
Price = 2	-.1345493***	-.0986007**	--	--
	(.0392424)	(.0461938)		
Price = 3	.0568035	.1894067***	--	--
	(.0454499)	(.0523184)		
Price = 4	-.0690678	.1102361*	--	--
	(.0527948)	(.062928)		
Category (*n* = 178)	Yes	Yes	No	No
Month	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Restaurant FE	**No**	**No**	**Yes**	**Yes**
Alpha	.7904929***	.8079081***	.7658407***	.7513479***
	(.0112651)	(.0126395)	(.0110396)	(.0121034)
Likelihood-ratio test	2.2e+04	1.7e+04	2.2e+04	1.6e+04
of alpha = 0	(P=0.000)	(P=0.000)	(P=0.000)	(P=0.000)
Log likelihood	-93868.968	-73993.32	-93444.683	-73335.644
LR χ^2	29416.07	19255.08	30264.64	20570.43
Pseudo R^2	0.1355	0.1151	0.1394	0.1230

Note: Values in parentheses indicate the *z* ratio. Asterisks indicate that the coefficient is significant at the *10%, **5%, and **1% level.

A summary of all hypotheses and the empirical support for each is presented in Table 3.9. Results indicate that all four hypotheses in the current study were empirically supported.

Table 3.9 Summary of Hypothesis-Testing Results

Hypothesis	**Empirical Support**
Hypothesis 1: Disconfirmation leads consumers to write reviews containing stronger sentiment (either positive or negative).	√
Hypothesis 2: Disconfirmation leads consumers to write longer reviews.	√
Hypothesis 3: Disconfirmation leads to more language reflecting causal-explanation processes in online review text.	√
Hypothesis 4a: The effects of positive and negative disconfirmation on review sentiment are asymmetrical; negative disconfirmation has a stronger effect than positive disconfirmation.	√
Hypothesis 4b: The effects of positive and negative disconfirmation on review length are asymmetrical; negative disconfirmation has a stronger effect than positive disconfirmation.	√
Hypothesis 4c: The effects of positive and negative disconfirmation on review causal-explanation content are asymmetrical; negative disconfirmation has a stronger effect than positive disconfirmation.	√

3.5 Discussion and Conclusion

Based on online review data from Yelp, this study examined the effects of rating disconfirmation on consumers' online review content characteristics and then investigated subsequent effects of review content characteristics on reviews' perceived usefulness. The following findings emerged. First, rating disconfirmation led consumers to write longer and more sentimental reviews and compelled consumers to explain in the body of the review why their opinions deviated from those of past consumers. Second, subsequent consumers perceived disconfirmed reviews as more useful. Third, disconfirmation effects exhibited negativity bias (i.e., the effect of negative rating disconfirmation was stronger than that of positive rating disconfirmation). Fourth, sentimental reviews, longer reviews, and reviews with more contents reflecting causal-explanation processes were perceived as more helpful by subsequent consumers. In sum, disconfirmed consumers tended to write more sentimental and longer reviews, including more contents reflecting causal-explanation processes, which led to higher review helpfulness. In other words, besides the direct effect of rating disconfirmation on review helpfulness, rating disconfirmation may also increase review helpfulness through changes in review content.

3.5.1 Theoretical Implications

The current research advances theoretical knowledge of consumer disconfirmation effects and review helpfulness. Specifically, this study contributes to the literature in three ways. First, this study contributes to research on the relationship between disconfirmation and consumers' post-purchase behavior by extending the influence of disconfirmation from an offline context to an online context. Prior literature focused largely on the effect of consumer disconfirmation in offline contexts, except for one recent study that examined the impact of disconfirmation on consumers' review-posting propensity and rating behavior using secondary data from an e-commerce website selling manufacturing products (Ho, Wu, & Tan, 2017). However, the influence of disconfirmation on online user-generated content has been largely overlooked in extant literature. This study marks the first attempt to investigate how disconfirmation effects manifest in terms of the textual characteristics of consumers' online reviews.

Second, this study enriches research regarding social influence effects on online consumer reviews. Early scholarship argued that online consumer-generated review information provides truthful feedback and unbiased reflections of consumers' product/service experiences (Hu, Liu, & Sambamurthy, 2011), whereas recent work has addressed the impact of posted reviews on subsequent ones from a social dynamic standpoint (Ho, Wu, & Tan, 2017; Lee, Hosanagar, Tan, 2015; Moe & Schweidel, 2012). The present work contributes to the latter literature stream by investigating the influence of rating disconfirmation (i.e., deviance between a consumer's post- consumption evaluation and the prior average review rating of the same product) on consumers' online review-writing behavior.

Third, this study contributes to the literature on online review helpfulness and associated influencing factors by proposing a new predictor: rating disconfirmation. This work also contributes to the literature on online review helpfulness and social influence. WOM literature commonly assumes that users' votes on reviews are based on their personal opinions. While this research extends previous literature by demonstrating that review usefulness votes are socially influenced and affected by the disconfirmation between a consumer's own product evaluation and review ratings posted by other consumers. In other words, a differentiated review rating can distinguish the corresponding review and garner more usefulness votes.

3.5.2 Managerial Implications

Findings from this study provide important managerial implications for online reputation systems and business marketers who attempt to interfere with online reviews. Professionals affiliated with these types of review platforms may wish to bear the following recommendations in mind.

Consumers should be asked to explain their reasons when submitting a disconfirmed review. Business marketers should encourage consumers with different opinions from the majority to provide clear and detailed reasons when consumers submit a disconfirmed review rating. This commentary will provide meaningful implication to the online review platform designer, who can redesign the system by identifying consumers who submit disconfirmed review ratings and by requiring these consumers to explain why their experiences differed from those of prior consumers.

Disconfirmed reviews containing strong sentiments and clear explanations for the deviation should be highlighted. The empirical results of this study show that rating disconfirmation causes reviews to receive more usefulness votes and compels consumers to write longer and more sentimental reviews clearly expressing their reasons for disconfirmation. These features positively influence the perceived usefulness of such reviews. Therefore, marketers should highlight disconfirmed reviews containing relatively strong sentiments and clear information explaining the deviation; for example, marketers could position these reviews prominently on the webpage.

Online review manipulation is detrimental to product eWOM. Online review manipulation in the hospitality industry is growing. In recent years, many business owners with a presence on third-party websites have posted fraudulent positive evaluations of their own products or negative reviews and ratings of competitors' products to better control their online reputation (Gormley, 2013; Ho, Wu, & Tan, 2017). Therefore, it is unsurprising that consumers are increasingly confused by deceptive review ratings and may make inaccurate purchase decisions as a result. According to the findings of this study, rating disconfirmation can lead consumers to write longer, more sentimental reviews with clear explanations for deviation, which subsequent consumers tend to perceive as more useful than reviews with less rating discrepancy. Therefore, these empirical findings can be used to understand how review manipulation influences subsequently posted reviews. Business marketers should understand that disconfirmed reviews will stand out and exert adverse effects on the reputation of a product/service in the long term.

3.5.3 Limitations and Future Research

Despite its revelations, this study has several limitations that can be addressed in future research. First, data were collected from one city and only applied to restaurants, limiting the generalizability of the findings. Future studies should further test these results with other hospitality/tourism products and in other cities. Second, this study did not verify whether consumers were aware of rating disconfirmations between their own evaluations and prior average review rating when posting their own restaurant reviews; therefore, future studies can explore this question by using an experimental design (e.g., a 2×1 between-subjects design in which one group of participants is exposed to review rating disconfirmation and the other is exposed to review rating confirmation). A comparison of participants' reviews from these two groups will address the abovementioned limitation. Third, the empirical approach used in this study did not reveal the underlying reasons explaining how disconfirmation affects consumers' online review behavior. Future studies can investigate this phenomenon by using qualitative methods such as interviews. The concepts identified in qualitative studies can then be empirically tested via an experimental design to determine the underlying mechanisms of disconfirmation effects. Fourth, this study did not test the moderating effects of certain restaurant attributes. The moderating effect of restaurant price range may reveal interesting influences of disconfirmation on the content characteristics of consumer-generated reviews. Potentially, the disconfirmation effect may only apply to restaurants with high prices and not to those with low prices. Finally, this study sample was derived from Western culture (i.e., the United States). Culture has been found to influence online reviews: Hong, Huang, Burtch, and Li (2016) used a TripAdvisor dataset and noted that compared to consumers from a collectivistic culture, those from an individualistic culture were more likely to deviate from prior average review ratings when expressing their experiences and emotions in written reviews. Similarly, Ho, Wu, and Tan (2017) argued that cultural factors influence consumers' willingness to disagree with others. Therefore, it is important to conduct a cross-cultural comparison study on this topic in the future.

CHAPTER 4

TO FOLLOW OTHERS OR BE YOURSELF? SOCIAL INFLUENCE EFFECTS ON ONLINE RESTAURANT REVIEWS

4.1 Introduction

Online reviews become increasingly popular as an important source of word-of-mouth (WOM). Consumers have come to rely heavily on online reviews to make purchase decisions (Dellarocas, 2006; Filieri, Alguezaui, & McLeay, 2015; Hu, Liu, & Sambamurthy, 2011), including holiday purchases (Sparks, Perkins, & Buckley, 2013; Xiang & Gretzel, 2010). Previous research has suggested that product sales and firms' financial performance are positively influenced by online reviews (Chevalier & Mayzlin, 2006; Ye, Law, & Gu, 2009; Zhu & Zhang, 2010). Therefore, understanding the factors that shape consumers' online review-rating behavior is essential.

Much extant literature assumes that online reviews provide an unbiased perspective on consumers' product experiences (Hu, Liu, & Sambamurthy, 2011). However, Moe and Schweidel (2012) and Schlosser (2005) argued that individuals tend to browse opinions expressed by past consumers on review pages when making their own rating decisions and then adjust their own evaluations accordingly; this phenomenon implies that consumers' online review ratings maybe socially influenced. According to anchoring effects in judgment, self-presentation, and social conformity theories, online product reviewers prefer to consider other group members' opinions when providing ratings (Adomavicius et al., 2013; Schlosser, 2005). Yet prior studies have revealed little regarding the social influence process involved in online review ratings as well as the factors that shape it (Moe & Schweidel, 2012; Sridhar & Srinivasan, 2012; Zhang, Zhang, & Yang, 2016), especially for experience-oriented hospitality products. Based on the following comprehensive literature review, several research gaps are identified.

First, consumers' product/service experiences can be heterogeneous, ranging from extremely positive or negative to moderately positive or negative. The social categorization literature suggests that compared to moderate-strength cues, extreme cues are considered more diagnostic and less ambiguous (Reeder & Brewer, 1979; Reeder, Henderson, & Sullivan, 1982; Skowronski & Carlston, 1989). Therefore, the degree to which heterogeneous product/service experiences are socially influenced by prior review ratings may differ. Second, according to social influence theory and the elaboration likelihood model (ELM), a consumer's online status matters and may affect consumers' decision-making process when rating a product/service. Ma et al. (2013) and Moe and Schweidel (2012) empirically tested the moderating effect of a user's review experience (measured by the number of reviews written by the reviewer) and found that consumers who had written fewer reviews were more likely to be socially influenced by prior review ratings. Nonetheless, the role of a reviewer's online status, which reflects the reviewer's expertise based on prior review quantity and quality (i.e., being labeled an expert—or not—on an online review website), has not been examined in current literature. Third, according to ELM, consumers who invest more cognitive effort into review writing are more likely to take a central thinking route. Ma et al. (2013) used review length to measure the cognitive effort invested in review writing and discovered that longer reviews can reduce the extent of social influence from prior reviews. However, review length is limited in representing cognitive efforts; further content and linguistic analyses of review text is needed to better examine a reviewer's cognitive effort.

By using online restaurant review data from Yelp, this study investigates whether and how prior review ratings posted by other consumers affect a focal consumer's online review-posting behavior in terms of his/her ratings regarding an experience-oriented product. In addition, this study examines the extent to which a consumer's experience extremity, cognitive effort in writing a review, online status, and the variance of prior review ratings influence his/her subsequent online review ratings. The findings from this study will contribute in several ways to the electronic word-of-mouth (eWOM) literature and social influence literature. First, this research will assess the bidirectional nature of social influence on eWOM for experience-oriented products; thus, online reviewers, who can influence others as opinion leaders, may also be socially influenced. Second, this study makes an initial attempt to examine the influence of prior reviews provided by other consumers on subsequent ratings of experience-oriented products and for consumers with various product/service experiences. Third, this study is among the first to examine the influence of prior reviews on subsequent review ratings for consumers with different online statuses (i.e., considered an expert/non-expert on an online review platform). Fourth, to the best of the author's knowledge, this study is the first to explore the moderating role of review characteristics using a text mining approach. The role of review texts remains unexplored in relevant literature, although text mining has developed rapidly and is now a popular research focus. This study proposes a new variable reflecting a reviewer's cognitive effort in writing reviews by counting all cognition-related words, drawing from previous literature in psychology that has framed language and words as indicative of cognitive effort.

Given the substantial influence of online review ratings on consumers' purchase decisions, willingness to pay, and business profitability, understanding the social influences on consumers' online review ratings is of paramount importance for business success. This research should help practitioners to better understand review-rating behavior and how ratings are socially influenced while also raising questions about the trustworthiness of online review ratings as an accurate index of product/service quality. Furthermore, the implications of this research advocate and provide guidelines for mitigating the social influence of prior reviews and improving the accuracy of online product/service ratings, which will eventually enhance business and the reputation of online review websites.

4.2 Literature Review and Research Hypotheses

Recent literature suggests that a consumer's subsequent review can be influenced by prior reviews read after product consumption (Lee, Hosanagar, & Tan, 2015; Ma et al., 2013; Moe & Schweidel, 2012; Moe & Trusov, 2011; Muchnik, Aral, & Taylor, 2013; Schlosser, 2005; Sridhar & Srinivasan, 2012; Wang, Zhang, & Hann, 2018), which may bias online product review ratings. Moe and Trusov (2011) noted that an online product rating is composed of the customer's actual consumption experience and social influence from prior reviews. Some literature notes that subsequent review ratings tend to imitate prior ratings, similar to a herding effect (e.g., Adomavicius, et al., 2013; Ma et al., 2013). Other scholars report that subsequent reviews tend to be differentiated from prior review ratings (i.e., a differentiation effect; e.g., Hu & Li, 2011; Moe & Trusov, 2011).

To address this contradiction, researchers have recently begun to examine the diverse impacts of prior review ratings given that reviewers and reviews are heterogeneous. For example, work by Ma et al. (2013) revealed that reviewers who wrote reviews less frequently tended to imitate prior reviews and ratings, whereas more seasoned reviewers were likely to post review ratings that were less socially influenced. Moe and Schweidel's (2012) study came to similar conclusions. Two recent studies revealed the distinct influences of prior reviews written by friends and strangers, such that a herding effect consistently characterizes friends' ratings, whereas those of strangers can induce herding or differentiate subsequent rating behavior (Lee, Hosanagar, & Tan, 2015; Wang, Zhang, & Hann, 2018). Relevant literature is summarized in Table 4.1.

4.2.1 Impact of Prior Reviews on Subsequent Review Ratings

Consumers usually check product reviews online before making purchases, which inform their pre-purchase expectations (Ho, Wu, & Tan, 2017). According to Hu and Li (2011), a consumer's expectations affect his or her subsequent satisfaction and evaluation of a product. Moreover, when customers visit a webpage to post an online review after making a purchase, they can see prior reviews and ratings from past customers (Moe & Schweidel, 2012; Schlosser, 2005). Moe and Trusov (2011) and Lee, Hosanagar, and Tan (2015) stated that an online product rating is comprised of a customer's real consumption experience and the degree of social influence on the consumer. Previous empirical studies have tested the influence prior reviews' characteristics on subsequent review ratings, but findings are inconsistent. For instance, Ma et al. (2013) identified herding behavior among subsequent reviewers. Based on book review data, Hu and Li (2011) noted that newly posted reviews are more likely to be differentiated from existing ones. More

Table 4.1 Summary of Previous Literature

Authors	**Title**	**Journal**	**Research Context**	**Method**	**Findings**
Schlosser (2005)	Posting versus lurking: Communicating in a multiple audience context	*Journal of Consumer Research*	Movie reviews	Laboratory experimental design	Reviewers who are expected to post their product experiences on the internet lower their online product ratings after reading others' negative reviews with the motivation of being perceived as discriminating or an expert, while no influence appears after reading positive reviews. Reviewers are more likely to present more than one side opinions than lurkers when they observe heterogeneous prior reviews.
Moe and Trusov (2011)	The value of social dynamics in online product ratings forums	*Journal of Marketing Research*	Reviews of bath, fragrance, and beauty products of an online retailer	Econometric model	Subsequent review ratings tend to be differentiated from prior review ratings. Discrepancies among prior raters discourage subsequent raters to post extreme opinions.
Hu and Li (2011)	Context-dependent product evaluations: An empirical analysis of internet book reviews	*Journal of Interactive Marketing*	Book reviews on Amazon.com	Econometric model, specifically the ordered logistic model	When product quality is controlled, subsequent review ratings tend to be differentiated from prior review ratings; this relationship is moderated by book popularity, variance of prior review ratings, and whether subsequent reviews mention previous reviews.

Authors	**Title**	**Journal**	**Research Context**	**Method**	**Findings**
Sridhar and Srinivasan (2012)	Social influence effects in online product ratings	*Journal of Marketing*	Hotel reviews (7499 reviews among 114 hotels)	Econometric model, specifically the nested ordered logistic model	Other consumers' review ratings moderate the effect of the focal consumer's product experience on his/her review rating for this product. The average review ratings of other consumers can weaken the relationship between "positive and negative attributes of product experience" and the consumer's review rating, while could strengthen or attenuate the negative impact of product failure on his/her rating, depending on the success of product recovery.
Godes and Silva (2012)	Sequential and temporal dynamics of online opinion	*Marketing Science*	Book reviews on Amazon.com	Econometric model, specifically the ordered logistic model	When controlling all other variables, online ratings for a product decrease over time. For a product with more ratings, subsequent ratings tend to be lower due to an increase in consumers' dissimilarity.
Moe and Schweidel (2012)	Online product opinions: Incidence, evaluation, and evolution	*Marketing Science*	Reviews of bath, fragrance, and home products from an online retailer	Two-stage econometric model: (1) selection model and (2) rating model	Positive ratings environments increase an individual's review-posting probability whereas negative ratings environments decrease it. Less frequent reviewers tend to imitate prior review ratings, and frequent reviewers tend to differentiate themselves by posting relatively negative ratings.
Ma, Khansa, Deng, and Kim (2013)	Impact of prior reviews on the subsequent review process in reputation systems	*Journal of Management Information Systems*	A panel data set of 61,029 reviews by 744 reviewers on Yelp	Econometric model: ordered probit model and Markov chain Monte Carlo simulation method	Male reviewers lacking review experience, social connection, or geographic mobility are more likely to be socially influenced by previous review ratings. More frequent and longer reviews tend to reduce the social influence of prior reviews.

Authors	Title	Journal	Research Context	Method	Findings
Muchnik, Aral, and Taylor (2013)	Social influence bias: A randomized experiment	*Science*	Social news aggregation website	A large-scale randomized experiment	Prior ratings exert social influence on subsequent individuals' rating behavior. For negative social influence, reviewers tend to correct biased ratings; positive social influence improves the positive ratings' probability, and subsequent review ratings increased by averagely 25%. However, social influence is topic-dependent and influenced by whether opinions of friends or enemies are observed.
Adomavicius, Bockstedt, Curley, and Zhang (2013)	Do recommender systems manipulate consumer preferences? A study of anchoring effects	*Information Systems Research*	Television shows or jokes	Laboratory experimental design	The rating displayed by a recommendation system can be an anchor, which influences viewers' preference ratings. This influence is also affected by perceived reliability of a recommendation system.
Lee, Hosanagar, and Tan (2015)	Do I follow my friends or the crowd? Information cascades in online movie ratings	*Management Science*	Movie reviews on several public websites	Two-stage econometric model: (1) selection model and (2) rating model (following Moe & Schweidel, 2012)	Friends' ratings can induce a herding effect (i.e., an individual reviewer tends to imitate his/her friends' ratings), and a larger number of friends (i.e., increased "audience size") can exert a positive effect on ratings. However, herding and differentiation effects influence crowd ratings (i.e., an individual reviewer tends to either imitate or differentiate him/herself from other strangers' ratings), depending on film popularity.

Authors	Title	Journal	Research Context	Method	Findings
Zhang, Zhang, and Yang (2016)	The power of expert identity: How website-recognized expert reviews influence travelers' online rating behavior	*Tourism Management*	Hotel reviews collected from Qunar.com	Econometric model: ordered logit model and Bayesian ordered logit model	The number of online user-generated “expert reviews” has a positive influence on subsequent reviewers’ ratings, whereas the marginal effect decreases. Reviewing expertise can strengthen this positive effect.
Wang, Zhang, and Hann (2018)	Socially nudged: A quasi-experimental study of friends' social influence in online product ratings	*Information Systems Research*	Reviews of books, movies, and music	Quasi-experiment (difference-in-difference)	Friend relationships can significantly improve online users’ rating similarity. Social influence is stronger for consumers with smaller online networks and for older books. More recent and extremely negative ratings show more salient influence than other reviews.

recently, Lee, Hosanagar, and Tan (2015) reported herding and differentiation behavior in crowd ratings of films depending on a movie's popularity, whereas friends' prior ratings consistently induced a herding effect. Given the disparities in these findings, an examination of social influence effects in online restaurant ratings will provide additional context.

According to social influence theory, people tend to experience conformity pressure from other group members (Cialdini & Goldstein, 2004). Darley and Latane (1968) argued that people conform to the social influence of peers with whom they are familiar as well as those they do not know. More recently, Cohen (2003) noted that people are also susceptible to the social influence of abstract reference groups. Reasons behind conformity behaviors include the following (Cialdini, 2009): (1) following others can lead to fewer mistakes; (2) following others is associated with lower mental effort; and (3) fear of losing reputation when deviating from most other group members.

According to anchoring effects in judgment (Chapman & Johnson, 2002; Tversky & Kahneman, 1974), people may apply an anchoring-and-adjustment heuristic when making a decision. The decision maker may begin with an initial value and make adjustments to reach a final choice. Other consumers' average rating constitutes an anchor or initial value, and then the focal consumer makes corresponding modifications according to the perceived disconfirmation based on his/her consumption experience. This leads the decision maker's final judgment to be skewed toward the anchor, as the anchoring effect tends to bias retrieval of previous experiences consistent with the initial anchor; anchoring effects in judgment are even more prominent when the experience/preference is recalled (Adomavicius et al., 2013). Adomavicius et al. (2013)

also found that a recommendation system rating tends to elicit anchoring bias and can significantly influence subsequent consumers' ratings of a product/service. Therefore, a consumer's online product rating is likely to be influenced by prior review ratings posted by other consumers. On this basis, the following hypothesis is proposed:

> Hypothesis 1 (H1): *The prior average review rating has a positive influence on the subsequent ratings of the same restaurant.*

4.2.2 Extremity Effect of Consumer Experience

A consumer's product experience can be heterogeneous, ranging from extreme (i.e., extremely positive or negative) to moderate (i.e., moderately positive or negative). Most judgments, such as like or dislike, imply an array of ratings with the level of judgment ambiguity determining the width of this range (Birnbaum, 1972; Wyer, 1974). When consumers have a moderate product experience with simultaneous positive and negative attributes, these customers are more likely to encounter uncertainty when quantifying the item's quality; that is, they may struggle to measure and rate product quality on a scale of 1–5 (or 1–10). Consumers will then search starting from the anchor to the plausible value in a distribution of uncertain values, leading to a final value that skews toward the anchor (e.g., Jacowitz & Kahneman, 1995). The correspondence judgment literature states that people are more confident in utilizing highly salient information, e.g., extreme opinions, which are often integrated into more formal judgments (Kruglanski, 1989). This uncertainty can be strengthened by preferences recalled from past experiences. Previous research (Cialdini, 2009; Cialdini & Goldstein, 2004; Walther et al., 2002) has shown that the uncertainty of an individual's judgment corresponds to a strong social influence, whereas certainty decreases social influence substantially. For instance, Hoch and Ha (1986) found that when consumers encounter ambiguous evidence, their product quality judgment depends on objective physical evidence as well as the dramatic influence imposed by advertising.

In contrast, according to the goal-based emotion literature, affective reactions of high intensity (e.g., extreme opinions) are only generated around important individual goals (Folkrnan & Lazarus, 1984; Lazarus, 1982). Extreme judgments tend to be considered more reliable and less ambiguous compared to moderate judgments, as extreme values only have a constricted range due to their locations at the scale end-point (Gershoff, Mukherjee, & Mukhopadhyay, 2003). When consumers face an extreme product experience, whether highly positive or negative, they are more likely to be certain in quantifying the quality on a scale of 1–5 (or 1–10). As such, regardless of other consumers' ratings, the focal consumer tends to quantify his/her experience with certainty (i.e., assigning a rating of 1 for an extremely negative experience or 5 for an extremely positive experience). In these cases, people may overlook conformity pressure and behave altruistically for the benefit of the group (Hornsey, 2006; Hornsey, Oppes, & Svensson 2002).

The social categorization literature indicates that compared to cues of extreme strength, moderate cues are perceived as more ambiguous and less reliable (Reeder & Brewer, 1979; Reeder, Henderson, & Sullivan, 1982). When consumers have an extremely positive or negative experience that disconfirms existing reviews and ratings, they are more likely to experience normative conflict and neglect conformity pressure if they believe doing so is better for the group (Ashforth, Kreiner, & Fugate, 2000). In this scenario, people are less likely to be socially influenced and will be motivated out of either concern for other consumers or an interest in helping the company by expressing a true product experience (Hennig-Thurau et al., 2004). Therefore, the following hypothesis is proposed:

> Hypothesis 2 (H2): *The influence of prior average review rating on subsequent ratings of the same restaurant is moderated by the extremity of a consumer's experience; the influence is stronger when the consumer has a moderate experience and weaker when the consumer has an extreme experience, either highly positive or negative.*

4.2.3 Consumer Cognitive Effort

Cognitive effort refers to "the total amount of cognitive resources, such as memory, perception, and judgment, needed to complete a task" (Russo & Dosher, 1983). Individuals' attempts to understand consumption experiences involve multiple cognitive processes, such as analytical writing (Lyubomirsky, Sousa, & Dickerhoof, 2006) and explanation (Malle, 2004; Moore, 2012). The cognitive processes can help people understand the causes and outcomes of their product/service experiences (Moore, 2012; Wilson & Gilbert, 2008). Joksimovic et al. (2014) found that participants exhibit better understanding if they are engaged in higher cognition and emotions while journaling about an experience. According to social conformity theory (Cialdini & Goldstein, 2004; Erb et al., 1998), if individuals expend little cognitive effort when processing a message, they are highly likely to use an accuracy heuristic favoring the group majority. Conformity could thus be the outcome of less-mindful activation of two conformity motivations, accuracy and affiliation, at little cost to cognitive resources (Chartrand & Bargh, 1999; Cialdini & Goldstein, 2004). According to ELM, consumers who invest extensive cognitive efforts when writing a product review attend to take a central route of thinking and thus rely less on other consumers' reviews and ratings when providing their own (Ma et al., 2013).

The psychology literature has considered language and words to be reflective of cognitive effort and processes (Joksimovic et al., 2014; Tausczik & Pennebaker, 2010). When individuals use cognitive mental processes in drafting online reviews, their comments exhibit a significant increase in words related to logical and analytical thought, such as *because*, *therefore*, and *think* (Ma et al., 2013). The presence of cognitive words in online reviews reflects the reviewer's analytical thought process and his/her active attempt to understand the experience, constituting a valid representation of the reviewer's underlying cognitive process (Boals & Klein, 2005). The following hypothesis is thus proposed:

> Hypothesis 3 (H3): *The influence of prior average review rating on subsequent ratings of the same restaurant is moderated by the consumer's cognitive effort in writing the online review; the influence is stronger for the consumer investing more cognitive effort in writing the review and weaker for the consumer investing less cognitive effort.*

4.2.4 Consumer Online Status

Given that consumers are heterogeneous in their online review experience, research has begun to examine the different impacts of prior review ratings on consumers' online evaluations among different reviewers. According to ELM (Bhattacherjee & Sanford, 2006; Petty, Cacioppo, & Schumann, 1983; Tam & Ho, 2005), individuals possess two routes for information processing: the peripheral route and the central route. ELM suggests that people who are more experienced tend to use the central route to process information and are less likely to be influenced by others. Those who are inexperienced are more likely to rely on others' opinions for reference when making a final decision (i.e., the peripheral route). Studies have reported that consumers with less review experience (measured by their number of reviews written previously) tend to mimic prior review ratings, whereas consumers with more review experience are more likely to post relative negative review ratings to differentiate themselves from others (Ma et al., 2013; Moe & Schweidel, 2012).

Most online review websites have developed reviewer-credentialing programs. Yelp has one such program in which reviewers can be certified as "Elite" if they have contributed substantially to the platform. The "Elite" label is not based solely on the number of reviews a reviewer writes but also well-written reviews, high-quality photos and tips, active voting behavior, and a history of being cordial to other users (Yelp, 2017). Connors, Mudambi, and Schuff (2011) found that reviews written by elite reviewers provide deeper insight into a product/service and are deemed more helpful. Compared to non-expert reviewers, experts often know more about a given product/service's intricacies and are better prepared to evaluate and recall their detailed experiences (Ma et al., 2013). Therefore, the author of the present study proposes that in addition to a reviewer's reviewing experience (as measured by the number of reviews previously written), a consumer's online status reflecting expertise (i.e., whether he/she is labeled an expert) moderates the impact of prior reviews on subsequent review ratings.

Hypothesis 4 (H4): *The influence of prior average review rating on subsequent ratings of the same restaurant is moderated by consumer online status; the* *influence is stronger when the consumer is not labeled an expert by the online review platform and weaker when the consumer is labeled an expert by the online review platform.*

4.2.5 Variance in Prior Review Ratings

Major e-commerce and online review websites, such as Amazon and Yelp, display the average rating of all consumers' reviews along with rating distributions, depicted by a bar chart indicating the number/proportion of each rating level (Sun, 2012). The bar chart often appears in a prominent location on the product introduction page (Sun, 2012) and is likely to be seen by a reviewer who may then be influenced by the distribution or variance of prior review ratings.

In the context of online reviews, the dispersion of ratings reflects reviewers' degree of consensus and provides information on the accuracy of the average rating (Yin, Mitra, & Zhang, 2016). Based on Bayesian information updating theory (Gelman et al., 2003), Hu and Li (2011) argued that among various information sources, those with lower variance exert greater impacts on consumers. In other words, highly dispersed review ratings reduce consumers' confidence in the certainty of the average rating (Petrocelli, Tormala, & Rucker, 2007). According to social conformity theory, consumers are more likely to be influenced by many peers whom share an opinion (Feldman, 2003; Lascu & Zinkhan, 1999). For example, consumers form an initial expectation about a hotel upon reading the average review rating, but this initial expectation could be attenuated when consumers are less certain about their initial beliefs (e.g., in the case of low review volume and high review dispersion). However, little is known about how online review rating distributions influence the impact of prior reviews on subsequent ratings, especially for restaurant online reviews. As such, the following hypothesis is proposed:

Hypothesis 5 (H5): *The influence of prior average review rating on subsequent ratings of the same restaurant is moderated by the variance in existing ratings; the influence is stronger when the variance is low and weaker when the variance is high.*

The research framework is summarized in Figure 4.1.

4.3 Research Method

4.3.1 Data

The restaurant setting, rather than manufactured goods, was used in this study as restaurant products are more experience-oriented with characteristics of intangibility, variability, perishability, and inseparability. Restaurant review data were collected from a popular online review website, Yelp.com, and Las Vegas was selected as the setting. The author chose the most popular 300 restaurants (measured by the number of online reviews) in Las Vegas to ensure a sufficient number of reviews per restaurant. All reviews for each restaurant were included in the dataset for a total of 186,714 reviews. Restaurants ranged from casual to fine dining, limited service to full service, and included all restaurant categories (e.g., American, Mexican, Italian). The sample also included all price ranges: inexpensive (n = 42, 13.96%), moderate (n = 184, 61.39%), pricey (n = 52, 17.26%), and ultra high-end (n =22, 7.39%).

4.3.2 Variable Operationalization

To assess the effects of prior average review rating on subsequent rating of the

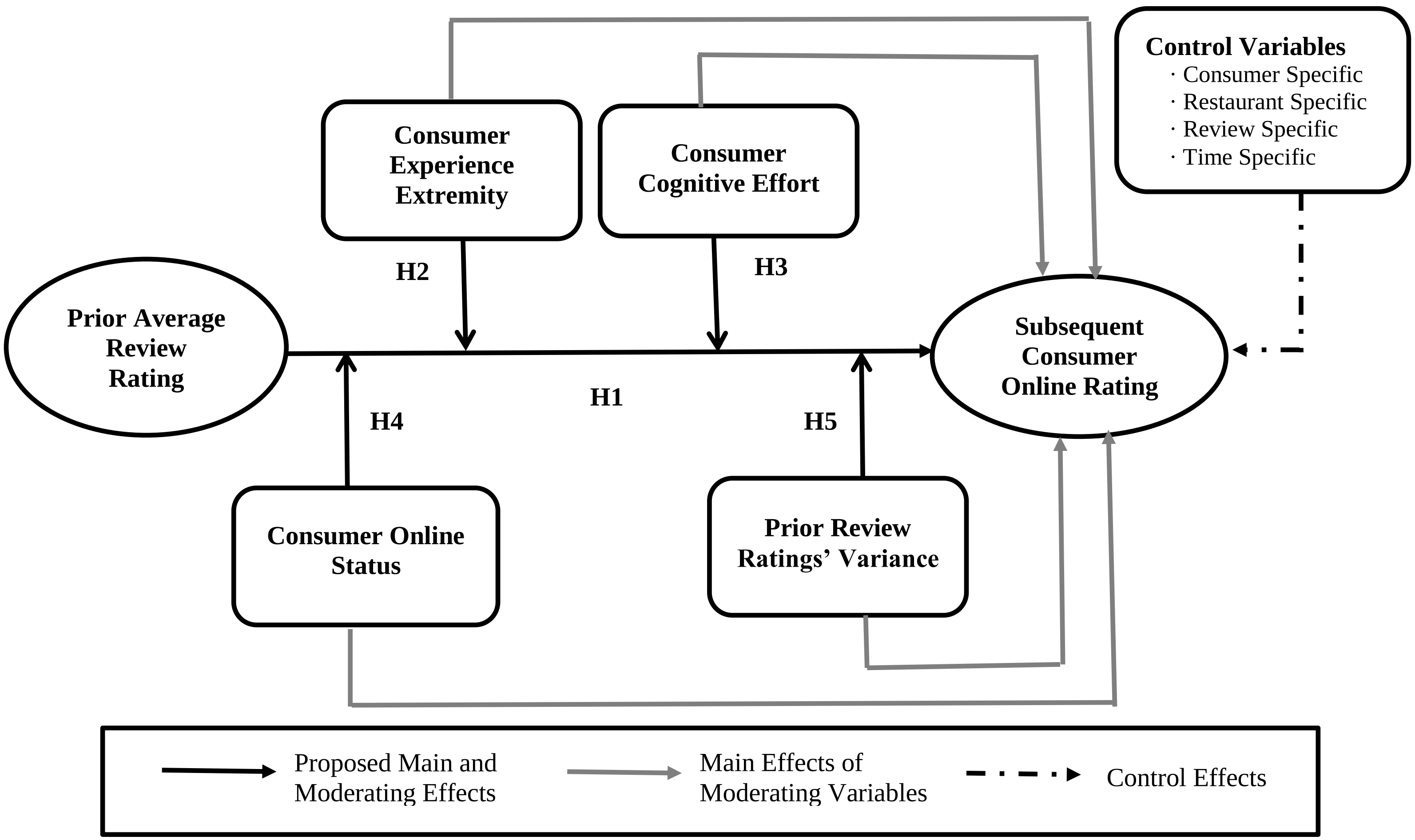

Figure 4.1 Conceptual Framework

same restaurant, a series of variables were incorporated and measured in the model. The dependent variable was the reviewer's online rating of the restaurant (y_{ijt}).

Prior average review rating. The average of prior restaurant review ratings before the current review (the *n*th review) was used to measure social influence (Sridhar & Srinivasan, 2012), taken as the average rating of the first, second, …, and $(n-1)$th review ratings for restaurant j ($AveOthers_{jt}$). Rather than the exact restaurant rating, the rounded average review rating to the nearest half-star as shown on Yelp was employed (Ma et al., 2013). The rounded average rating is consistent with that displayed on Yelp and allowed the author to accurately test the social influence of prior review ratings.

Consumer experience extremity. Consistent with Sridhar and Srinivasan (2012) and Ma et al. (2013), words/emotions in online review text reflect consumers' real product experiences. Consumer experience extremity ($ConsExp_{ijt}$) was measured by calculating the sentiment index for a review. *Sentiment* refers to an attitude, thought, or judgment prompted by a feeling. This study calculated review sentiment using the naïve Bayesian algorithm (McCallum & Nigam, 1998)[1], one of the most widely recognized text categorization methods. The values of review sentiment ranged from 0–1; the higher the sentiment value, the more positive the experience. Consumer experience extremity in this study was coded as 1 if the value was smaller than 0.05, meaning extreme negative experience; it was coded as 2 if the value was larger than 0.95, meaning extreme positive experience; otherwise, it was coded as 0.

[1] A support vector machine (SVM) classifier was also used to calculate review sentiment in this study, but its performance was worse than a naïve Bayes classifier. Therefore, the naïve Bayes algorithm was finally adopted to calculate review sentiment.

Cognitive effort. The latest version of the Linguistic Inquiry and Word Count (LIWC) program, a text mining tool, was used to analyze the percentage of cognitive process words (e.g., *because*, *cause*, *know*, *ought*) in the body of each review (Pennebaker, Tormala, & Rucker, 2007), especially causal (e.g., *because, hence*) and insight-related words (e.g., *consider*, *think*, *know*). The LIWC program calculates the percentage of words matched to pre-defined dictionaries in a text (Pennebaker, Tormala, & Rucker, 2007). More cognitive-related words in review text suggest that more cognitive efforts were devoted to review writing. In addition to the frequent use of LIWC in psychology, the program has garnered increasing attention in marketing (Ludwig et al., 2013; Sridhar & Srinivasan, 2012) and information systems research (Goes et al., 2014; Hong et al., 2016; Yin et al., 2014).

Consumer online status. Consumer online status was coded as 1 if the consumer was an elite reviewer in the year the review was written; otherwise, it was coded as 0.

Variance of prior review ratings. The variance of prior review ratings ($ReviVar_{jt}$) was measured by the variance of the first, second, …, and $(n-1)$th review ratings for restaurant j (before current review n).

Control variables. To ensure an unbiased estimation, the author needed to control for all other alternative explanations. Therefore, review length ($Length_{ijt}$) was controlled in the model. In terms of reviewer-specific variables, reviewer tenure ($Tenure_{it}$), as measured by the number of days since the consumer's website registration, was included in the model as a control variable. The number of review ratings for restaurant j at time t (before the current review) ($Volume_{jt}$) was included to control the restaurant popularity effect. Moreover, two variables were included in the model to control for unobserved restaurant heterogeneity, which was invariant with time. First, the price range of the restaurant ($Price_j$) was controlled to account for the possible role of price sensitivity. Second, restaurant category ($Category_j$), such as American, Mexican, or Chinese, was controlled because consumers' cuisine preferences may affect restaurant evaluation and review writing. Time heterogeneity (Godes & Silva, 2012; Ma et al., 2013) was also considered, and the time effect was controlled by a series of dummy variables reflecting the year ($Year_{ijt}$) and month ($Month_{ijt}$) when the review was posted on Yelp. Ratings across different years, months, and days of the week could be different due to unobserved shocks, trends or seasonal effects. The details for each variable are listed in Table 4.2; summary statistics appear in Table 4.3.

Table 4.2 Variable Operations

Variable	Description
Dependent variables	
y_{ijt}	Review rating provided in review i for restaurant j at time t
Independent variables	
$AveOthers_{jt}$	The prior average review rating for restaurant j at time t (before the current review)
Control variables	
(1) Review-level	
$Length_{ijt}$	Total number of words in review i for restaurant j at time t
(2) Reviewer-level	
$Tenure_{it}$	Number of months since the consumer registered on Yelp when review i was written at time t
(3) Restaurant-level	
$Popularity_{jt}$	Number of reviews for restaurant j at time t (before the current review)
$Price_j$	A categorical variable classifying restaurants into different price ranges (1 = inexpensive; 2 = moderate; 3 = pricey; 4 = ultra high-end)
$Category_j$	A categorical variable classifying restaurants into different categories (*n* = 178)

Variable	Description
(4) Time-level	
$Year_{ijt}$	Year in which review was written (reference year = 2005)
$Month_{ijt}$	Month in which review was written (reference year = January)
Moderators	
$ExpExtremity_{ijt}$	Consumer i's experience extremity for restaurant j at time t (1 = sentiment value either smaller than 0.05 or larger than 0.95; otherwise, equals 0)
$Cognitive_{ijt}$	Consumer i's cognitive effort, measured by the proportion of cognitive process words (e.g., *because*, *cause*, *know*, *ought*) in each review text by consumer i for restaurant j at time t
$Status_{it}$	Consumer i's online status, measured by whether consumer i was labeled "Elite" in year t when writing a review (yes = 1; no = 0)
$Variance_{jt}$	Variance of review ratings for restaurant j at time t (before the current review)

Table 4.3 Variable Descriptions

Variable	Mean	Std. Dev.	Min	Max
Dependent variable				
y	3.847258	1.198129	1	5
Independent variable				
AveOthers	3.882435	.4733675	1.5	5
Moderating variable				
ExpExtremity	--	--	0	1
Cognitive	9.987555	4.514909	0	100
Status	--	--	0	1
Variance	1.110787	.328854	0	8
Control variable				
Length	134.2243	120.8954	1	1015
Tenure	22.81882	19.61112	0	117
Popularity	526.5275	614.0053	0	4136
Price	--	--	1	4
Category	--	--	1	178
Year	--	--	2004	2015
Month	--	--	1	12

4.3.3 Econometric Model

To evaluate overall restaurant quality, the Yelp community uses a product rating system with an integer value ranging from 1–5. Because the dependent variable was ordinal and consisted of censored data, an ordered logit model was used in this study (Cameron & Trivedi, 2005). The basic analytic unit was the review. Consider a review rating $y_{ijt} = \{1,2,3,4,5\}$, which is the rating score written by consumer i ($i = 1, \dots, I$) for restaurant j ($j = 1, \dots, J$) at time t. Let $y_{ijt}{}^{*}$ be the latent variable that represents the consumer's restaurant evaluation. $y_{ijt}{}^{*}$ is specified as a function of different factors that can affect the customer's evaluation as follows:

$$\begin{aligned} y_{ijt}{}^{*} = {} & \alpha_0 \mathrm{AveOthers}_{jt} \\ & + \beta_1 \mathrm{ExpExtremity}_{ijt} + \beta_2 \mathrm{Cognitive}_{ijt} + \beta_3 \mathrm{Status}_{it} + \beta_4 \mathrm{Variance}_{jt} \\ & + \gamma_1 \mathrm{AveOthers}_{jt} \times \mathrm{ExpExtremity}_{ijt} + \gamma_2 \mathrm{AveOthers}_{jt} \times \mathrm{Cognitive}_{ijt} \\ & + \gamma_3 \mathrm{AveOthers}_{jt} \times \mathrm{Status}_{it} + \gamma_4 \mathrm{AveOthers}_{jt} \times \mathrm{Variance}_{jt} \\ & + \theta' \mathrm{Z}_{ijt} + \varepsilon_{ijt} \,, \end{aligned} \tag{1}$$

where Z_{ijt} represents the other control variables described above, and ε_{ijt} is an error term with a logistic distribution of $\mathrm{F(z)} = \mathrm{e^z}/(1 + \mathrm{e^z})$.

As $y_{ijt}{}^{*}$ crosses a series of increasing unknown thresholds, the ordering of alternatives moves up accordingly. The ordered model in this study is defined as follows (Cameron & Trivedi, 2005):

$$\begin{aligned} \Pr\left[\mathrm{Rating}_{ijt} = j\right] & = \Pr[\alpha_{m-1} < y_{ijt}{}^{*} < \alpha_m] \\ & = \Pr[\alpha_{m-1} < x'_{ijt}\beta + u_{ijt} < \alpha_m] \\ & = \Pr[\alpha_{m-1} - x'_{ijt}\beta < u_{ijt} < \alpha_m - x'_{ijt}\beta] \end{aligned}$$

$$= \mathrm{F}(\alpha_m - x'_{ijt}\beta) - \mathrm{F}(\alpha_{m-1} - x'_{ijt}\beta), \quad (2)$$

where F is the cdf of u_{ijt}.

The threshold values (α_m) and regression parameters β can be obtained using the maximum log-likelihood estimation method with Equation (2).

4.4 Empirical Results

4.4.1 Main Results

The estimation results of the ordered logit model are shown in Table 4.4. Model 1.1 only included a series of control variables as the independent variable. Model 1.2 tested the effect of the prior average review rating on the subsequent review rating while controlling all control variables included in Model 1.1. Model 1.3 was the full model incorporating Model 1.2 and tested the moderating effects of the consumer's experience extremity, cognitive effort, online status, and variance of prior review ratings. The estimation results among the three models were consistent. Model 1.3 had the highest pseudo R^2 value (0.1601) and was thus used in the following sections to explain the final estimation results.

According to Model 1.3 (Table 4.4), the effect of prior average review rating exerted a significant and positive influence on the subsequent restaurant rating (coefficient = 1.451363); hence, H1 was supported. The influence of the prior average review rating on the subsequent rating was negatively moderated by the consumer's experience extremity (extreme negative experience: coefficient = -0.5802659, $p < 0.000$; extreme positive experience: coefficient = -0.1900039, $p < 0.000$). In other words, the social influence of prior average review rating was weaker when the consumer had either an extreme negative experience or positive experience, and social influence was stronger when the consumer's dining experience was moderate; thus, H2 was supported.

Regarding the role of consumer cognitive effort, the estimation results demonstrate that the moderating effect was significant but negative (coefficient = -0.0115263), indicating that the social influence from the prior average review rating was weaker when a consumer invested substantial effort in writing the review. Social influence was stronger when a consumer devoted less effort. H3 was therefore supported.

For reviewer online status, the estimation results demonstrate a significantly negative moderation effect (coefficient = -0.1607279, $p < 0.01$), indicating that non-elite reviewers were more likely to be socially influenced by the prior average review rating, whereas elite reviewers were less likely to be socially influenced; therefore, H4 was supported. The moderating effect of the variance in existing review ratings was found to be significant and negative (coefficient = -0.1492984). The influence was thus stronger when the variance of existing restaurant review ratings was low and weaker when the variance was high, supporting H5.

Table 4.4 Estimation Results—Ordered Logit Model

	Model 1.1	Model 1.2	Model 1.3
AveOthers		1.128559*** (.0150197)	1.451363*** (.0479882)
ExpExtremity			
Low (= 1)			-.0511321 (.1171615)
High (= 2)			2.017633*** (.0834556)
ExpExtremity × *AveOthers*			
Low (= 1) × *AveOthers*			-.5802659*** (.0312033)
High (= 2) × *AveOthers*			-.1900039*** (.0215297)
Cognitive			-.0123731 (.0082127)

	Model 1.1	Model 1.2	Model 1.3
Cognitive × AveOthers			-.0115263***
			(.0021199)
Status			.5139996***
			(.0831501)
Status × AveOthers			-.1607279***
			(.0215101)
Variance			.4374829***
			(.1142373)
Variance × AveOthers			-.1492984***
			(.0295331)
Length	-.0016519***	-.0017552***	-.0012144***
	(.0000367)	(.0000369)	(.0000401)
Tenure	-.0031177***	-.0032814***	-.0031168***
	(.0002348)	(.0002356)	(.0002502)
Volume	-.00005***	-.0001243***	-.0001024***
	(.000012)	(.0000121)	(.0000125)
Price			
Price = 2	-.5382833***	-.1339934***	-.2063145***
	(.033001)	(.0336871)	(.035647)
Price = 3	-.0715256*	.0874415**	-.0911626**
	(.0386503)	(.0388968)	(.0412116)
Price = 4	-.0508706	.0660336	-.092124*
	(.0465049)	(.046919)	(.0490198)
Restaurant Category	Yes	Yes	Yes
Review Year FE	Yes	Yes	Yes
Review Month FE	Yes	Yes	Yes
/cut-1	-2.756608*	1.788264***	2.093023***
	(1.514044)	(.3372759)	(.5202077)
/cut-2	-1.725567	2.834868***	3.470285***
	(1.514026)	(.337251)	(.5201699)
/cut-3	-.7566665	3.825315***	4.809533***
	(1.514017)	(.3372979)	(.5202089)
/cut-4	.7099148	5.325628***	6.613248***
	(1.514018)	(.3374146)	(.5203075)
Observations	186,566	186,256	185,969
Pseudo R^2	0.0432	0.0540	0.1601
LR χ^2	22757.49	28443.46	84143.82
Prob > χ^2	0.0000	0.0000	0.0000
LL	-252184.9	-248943.93	-220701.4

Note: Values in parentheses indicate standard errors. Asterisks indicate the coefficient is significant at the *10%, **5%, and **1% level.

Estimation results regarding the influences of control variables on a consumer's online restaurant review rating were consistent and robust in Model 1.1–Model 1.3. In Model 1.3, review length had a significant and negative influence on a consumer's online review rating (coefficient = -0.0012144), indicating that consumers may write more in online reviews when complaining about an unpleasant dining experience. The effect of consumer tenure on Yelp also showed a significantly negative influence on a consumer's online review rating (coefficient = -0.0031168); that is, consumers who had been members of Yelp for a longer time were more likely to assign a restaurant a lower rating. In addition, the number of prior review ratings exerted a significantly negative impact (coefficient = -0.0001024, $p < 0.001$), implying that the restaurant rating decreased with an increase in the number of online reviews. This result is consistent with the self-selection bias proposed by Li and Hitt (2008), noting that early consumers self-select products they believe they may enjoy and thus tend to provide higher ratings compared to subsequent consumers and the general population.

4.4.2 Robustness Check

Alternative Operations of Variable. To examine model robustness, the sensitivity of the estimation results to different operations of experience extremity was checked using two alternative operations. First, consumer experience extremity was coded as 1 if the value was smaller than 0.01, meaning extreme negative experience; it was coded as 2 if the value was larger than 0.99, meaning extreme positive experience; otherwise, it was coded as 0. Second, consumer experience extremity in this study was coded as 1 if the value was smaller than 0.10, meaning extreme negative experience; it was coded as 2 if the value was larger than 0.90, meaning extreme positive experience; otherwise, it was coded as 0. Then, the new models were re-estimated by replacing consumer experience extremity with the above two alternative operations. Results in Table 4.5 are quantitatively similar to those in Table 4.4.

Table 4.5 Estimation Results—Alternative Measurement for *ExpExtremity*

	Model 2.1 (0.01, 0.99)	Model 2.2 (0.10, 0.90)
AveOthers	1.452006*** (.0468424)	1.410545*** (.0488862)
ExpExtremity		
Low (= 1)	-.1556163 (.1283528)	-.0979475 (.1165062)
High (= 2)	2.153921***(.0794366)	1.852866*** (.0894302)
ExpExtremity × *AveOthers*		
Low (= 1) × *AveOthers*	-.63068*** (.0343093)	-.5130765*** (.0309526)
High (= 2) × *AveOthers*	-.227879*** (.0204043)	-.1407263*** (.0231411)
Cognitive	-.0101047 (.0082058)	-.016944** (.0082024)
Cognitive × *AveOthers*	-.0127141*** (.0021177)	-.0099128*** (.0021177)
Status	.5316952*** (.0828544)	.5038634*** (.0832294)
Status × *AveOthers*	-.1668433*** (.021439)	-.1556435*** (.021529)
Variance	.4273666*** (.1139828)	.4426208*** (.1141778)
Variance × *AveOthers*	-.1486759*** (.0294648)	-.1525343*** (.0295325)
Length	-.0014508*** (.0000407)	-.001119*** (.0000398)
Tenure	-.0032291*** (.0002502)	-.0030419*** (.0002501)
Volume	-.0000954*** (.0000125)	-.0001071*** (.0000125)
Price		
Price = 2	-.2058639*** (.0355588)	-.2147045*** (.0356891)
Price = 3	-.0940282** (.0411259)	-.0912189** (.0412515)
Price = 4	-.0815797* (.0489564)	-.0848535*(.0490237)
Restaurant Category	Yes	Yes
Restaurant FE	No	No
Review Year FE	Yes	Yes
Review Month FE	Yes	Yes
/cut-1	1.760366*** (.514159)	2.090215*** (.5155481)
/cut-2	3.119931*** (.5141095)	3.461095*** (.5155182)
/cut-3	4.411374*** (.5141292)	4.811582*** (.5155656)
/cut-4	6.18729*** (.5142289)	6.62361*** (.5156594)
Observations	185969	185,969
Pseudo R^2	0.1523	0.1614
LR χ^2	80032.72	84834.02
Prob > χ^2	0.0000	0.0000
LL	-222756.95	-220356.3

Note: Values in parentheses indicate standard errors. Asterisks indicate the coefficient is significant at the *10%, **5%, and **1% level.

Table 4.6 Estimation Results—Robustness Check with Restaurant Fixed Effects

	Model 3.1	Model 3.2	Model 3.3
	(0.95, 0.05)	(0.99, 0.01)	(0.90, 0.10)
AveOthers	.8673359***	.8587205***	.8343061***
		(.053343)	(.0551583)
ExpExtremity			
Low (= 1)	-.0572254	-.1614351	-.1045452
	(.1171526)	(.1283907)	(.1165009)
High (= 2)	2.033943***	2.177803***	1.865575***
	(.0839782)	(.0800483)	(.0898701)
ExpExtremity × *AveOthers*			
Low (= 1) × *AveOthers*	-.5780882***	-.6282594***	-.5106914***
	(.031206)	(.0343235)	(.0309558)
High (= 2) × *AveOthers*	-.1927172***	-.2322177***	-.1428145***
	(.021666)	(.0205621)	(.0232573)
Cognitive	-.0144061*	-.0120238	-.0187978**
	(.0082436)	(.0082369)	(.008234)
Cognitive × *AveOthers*	-.0110753***	-.0122827***	-.009515***
	(.0021278)	(.0021257)	(.0021258)
Status	.4436789***	.4605722***	.434039***
	(.0834408)	(.0831559)	(.08352)
Status × *AveOthers*	-.1391766***	-.1451602***	-.1342107***
	(.0215901)	(.0215217)	(.0216088)
Variance	.5520251***	.5164394***	.5760351***
	(.134435)	(.1337551)	(.134285)
Variance × *AveOthers*	-.1976034***	-.1905214***	-.2039917***
	(.0357003)	(.0355254)	(.0356785)
Length	-.0013245***	-.0015605***	-.0012284***
	(.0000404)	(.000041)	(.0000401)
Tenure	-.0032126***	-.0033208***	-.0031436***
	(.0002513)	(.0002513)	(.0002512)
Volume	-.0001598***	-.000152***	-.0001642***
	(.0000158)	(.0000158)	(.0000158)
Price	No	No	No
Restaurant Category	No	No	No
Restaurant FE	Yes	Yes	Yes
Review Year FE	Yes	Yes	Yes
Review Month FE	Yes	Yes	Yes
/cut-1	-.6493999	-1.026319	-.5857437
	(.5359998)	(.5310995)	(.5288668)
/cut-2	.7317343	.3365711	.7892033
	(.5359522)	(.5310413)	(.5288257)
/cut-3	2.077409***	1.634572***	2.145956***
	(.5359694)	(.5310389)	(.5288517)
/cut-4	3.894637***	3.424235***	3.971123***
	(.536013)	(.5310816)	(.5288917)

	Model 3.1 (0.95, 0.05)	Model 3.2 (0.99, 0.01)	Model 3.3 (0.90, 0.10)
Observations	185,969	185,969	185,969
Pseudo R^2	0.1634	0.1556	0.1647
LR χ^2	85879.65	81786.61	86539.02
Prob > χ^2	0.0000	0.0000	0.0000
LL	-219833.48	-221880	-219503.8

Note: Values in parentheses indicate standard errors. Asterisks indicate the coefficient is significant at the *10%, **5%, and **1% level.

Robustness Test Using Restaurant Fixed Effects. In addition to the price and restaurant categories, which may affect a consumer's online review rating, other restaurant-level variables (e.g., location, parking, and transportation) can also influence a consumer's evaluation. To avoid estimation bias, another robustness check was conducted by replacing restaurant-level variables of price and category with restaurant fixed effects to help control for unobserved time invariant heterogeneity. Estimation results are listed in Table 4.6 and are quantitatively similar to the main estimation results.

All hypotheses were empirically supported and appear in Table 4.7.

Table 4.7 Summary of Hypothesis-Testing Results

Hypothesis	**Empirical Support**
Hypothesis 1 (H1): The prior average review rating has a positive influence on the subsequent rating of the same restaurant.	√
Hypothesis 2 (H2): The influence of prior average review rating on subsequent ratings of the same restaurant is moderated by the extremity of a consumer's experience; the influence is stronger when the consumer has a moderate experience and weaker when the consumer has an extreme experience, either highly positive or negative.	√
Hypothesis 3 (H3): The influence of prior average review rating on subsequent ratings of the same restaurant is moderated by the consumer's cognitive effort in writing the online review; the influence is stronger for the consumer investing more cognitive effort in writing the review and weaker for the consumer investing less cognitive effort.	√

Hypothesis	**Empirical Support**
Hypothesis 4 (H4): The influence of prior average review rating on subsequent ratings of the same restaurant is moderated by consumer online status; the influence is stronger when the consumer is not labeled an expert by the online review platform and weaker when the consumer is labeled an expert by the online review platform.	√
Hypothesis 5 (H5): The influence of prior average review rating on subsequent ratings of the same restaurant is moderated by the variance in existing ratings; the influence is stronger when the variance is low and weaker when the variance is high.	√

4.5 Conclusion and Discussion

Using online restaurant review data from Yelp, this study examined whether and how prior review ratings posted by other consumers affect a subsequent consumer's online review-posting behavior when evaluating an experience-oriented product such as a restaurant. The industry would benefit from a clearer understanding of the factors that can decrease social influence to ensure accurate product evaluations; therefore, this study investigated the roles of consumer experience extremity, cognitive effort in writing a review, online status, and variance of prior review ratings in consumers' restaurant online reviews. The author turned to social influence and online WOM literature to formulate hypotheses and tested them using a large online dataset and text mining approach. The empirical results indicate that (1) prior average review rating exerts a positive influence on subsequent review ratings for the same restaurant; (2) the influence of prior average review ratings on subsequent ratings is stronger when the consumer has a moderate dining experience or invests less cognitive effort in writing the review, whereas the influence is weaker when the consumer has an extreme dining experience or devotes more cognitive effort to writing the review; (3) compared with elite reviewers, non-elite reviewers on an online review platform are more susceptible to the social influence of prior average review ratings; and (4) the effect of social influence is attenuated by the variance in existing review ratings.

4.5.1 Theoretical Implications

This study contributes to the previous literature in several ways.

First, it is one of the few in hospitality and tourism to document the bidirectional nature of social influence on eWOM for experience-oriented products. Online reviewers, who influence others as opinion leaders, may also be socially influenced. Marketers and online review websites should understand that consumers' online reviews and ratings are not independent or based solely on their consumption experiences; rather, consumers' ratings are socially influenced to some extent by prior reviews from earlier consumers.

Second, this study made an initial attempt to examine the influence of prior reviews on subsequent review ratings of the same restaurant for consumers with heterogeneous product experiences. This conclusion extends previous studies on social influence and online review ratings (Hu & Li, 2011; Ma et al., 2013) in which heterogeneous consumer consumption experiences were not considered.

Third, this study is among the first to examine the influence of prior reviews on subsequent review ratings for consumers with different online statuses (i.e., elite vs. non-elite) on an online review website. The finding of this study was somewhat consistent with that of Ma et al. (2013), who found that online reviewers with more reviewing experience and bigger social network did not tend to be influenced by prior online reviews.

Fourth, to the best of the author's knowledge, this study is the first to examine the moderating role of review characteristics using a text mining approach. A new variable reflecting a reviewer's cognitive effort in writing a review was considered by counting all cognitive-related words, a technique that first appeared in psychological studies applying language as a significant indicator of cognitive effort. The present work also complements a study from Ma et al. (2013) investigating the moderating variable of review length.

4.5.2 Managerial Implications

The objective of a reputation system is to provide true quality evaluations of products/services (Ma et al., 2013); therefore, highlighting biased online reviews or filtering out biases is critical for reputation systems as well as for consumers seeking to make well-informed purchase decisions. This study identified several measurable conditions under which subsequent review ratings are more likely to be socially influenced. The findings of this study yield the following important managerial implications for practice.

First, the empirical findings provide valuable insight for the designers of online review platforms. Such platforms can construct indices related to the factors specified in this study to rank the reliability of reviewers and their reviews. Using this type of ranking system would encourage reviewers to invest more cognitive effort in drafting comprehensive and objective reviews, while also filtering out biases to ensure accurate reflections of their consumption experiences. These measures should benefit online review platforms in the long term.

Second, online review platforms can develop algorithms to recommend reviews free from social influence for each business. Highlighting these reviews and placing them in more prominent webpage locations would aid consumers in making better purchase decisions. Online review platforms could also post a warning if a review appears to be strongly biased or socially influenced.

Third, reviews and their corresponding ratings are not created equal. For example, the present study found systematic differences between elite and non-elite reviewers in terms of their online review-rating behaviors. Compared with non-elite reviewers, ratings posted by elite reviewers were more resistant to social influence; therefore, online reviews written by elite reviewers were more likely accurately depict their real consumption experiences. If the ultimate goal of an online reputation system is to provide unbiased reflections of product quality, then when using consumers' collective wisdom, system designers should assign more weight to review ratings provided by elite reviewers and discount those from non-elite reviewers.

4.5.3 Limitations and Future Research

This study is subject to several limitations and raises a few interesting questions that warrant further exploration. First, although this research model incorporated many important factors associated with social influence in online reviews, many other characteristics pertaining to the reviewer and the review text were unaccounted for. Future studies can test the roles of these characteristics, such as reviewers' social networks and their perceived power. Ma et al. (2013) argued that social networks and social connectedness may influence reviewers' online review-rating decisions. The current study only tested the role of reviewers' online status, and it would be a promising topic to explore how reviewers' social networks shape their rating decisions. Second, this study neglected time delays after consumer's restaurant dining experiences and automatically assumed that consumers posted reviews immediately after dining. Yet according to memory strength theory (Hinrichs, 1970), the duration between the time of a dining experience and the publication of a corresponding review could affect how the dining experience is recalled and, by extension, the overall evaluation. Therefore, future studies may wish to investigate the impact of time duration between consumption and a corresponding review when such data are available. Third, this study assumed that the social influence of consumers' online review ratings was not affected by the technologies used to read and post online reviews. Webpage designs and consumers' reading habits vary on smartphones/tablets versus personal computers; therefore, future studies could test the moderating effect of reviewers' technologies on their review ratings. Fourth, similar to Li and Hitt (2008), the current work did not differentiate the effects of prior reviews and self-selection on subsequent consumers' online review behaviors. This topic would be interesting to explore in subsequent research, particularly the effects of prior reviews when controlling for consumer self-selection. An experimental design may provide additional insight into a true causality effect.

CHAPTER 5

GENERAL CONCLUSIONS

5.1 Research Conclusion

Understanding the factors influencing consumers' online review behavior is crucial for hospitality business success and related scholarship. This dissertation has examined online review behavior from the angle of the social influence of prior reviews. The preceding chapters explored how prior review ratings and disconfirmation influenced consumers' online review-posting behavior in terms of their willingness to post online reviews, their final review rating decisions, and the textual content characteristics of reviews.

Study 1 completed a series of three experiments to empirically test the effects of disconfirmation on consumers' willingness to post online reviews and review rating decisions in the context of a hotel and restaurant, respectively. In the hotel scenario, Experiment 1 investigated the direct influence of disconfirmation on consumers' willingness to post online reviews. Experiment 2 was conducted within a restaurant context to examine the indirect effect of disconfirmation on consumers' willingness to post online reviews out of concern for other consumers. Experiment 3 used a hotel context to examine the direct and indirect effects of disconfirmation on consumers' review ratings as well as the moderating effect of prior review ratings' variance on the influence of disconfirmation on consumers' willingness to post online reviews and review ratings.

Based on 300 restaurant online reviews from Las Vegas, Study 2 assessed the influences of disconfirmation on consumers' online review content characteristics. The influences of disconfirmation on review length, review sentiment, and review content reflecting a causal-explanation process were investigated. This study also explored whether and how disconfirmation influences perceived review usefulness. Borrowing from negativity bias theory, the asymmetrical effects of positive and negative disconfirmation on review content characteristics and perceived review usefulness were also tested.

Study 3 examined whether and how consumers' prior average review rating influences subsequent consumers' online review ratings for the same restaurant. By applying an ordered logit model to online reviews from 300 restaurants in Las Vegas, this study evaluated the direct effect of prior average review rating on subsequent consumers' review ratings for the same restaurant and examined the moderating effects of consumer experience extremity, cognitive effort in writing a review, consumer online status, and prior review ratings' variance as contributors to the social influence process.

The results of this dissertation can be summarized as follows. First, disconfirmation (vs. confirmation) was found to lead to increased willingness to post online reviews. Consumers tended to show stronger willingness to post online reviews when their post-consumption evaluations deviated from prior average review ratings for the same hotel or restaurant. In contrast, consumers were more likely not to contribute to an online review platform if their post-consumption evaluations were similar to prior average review ratings. The motivation of concern for others increased significantly when consumers encountered disconfirmation and led to increased willingness to post online reviews.

Second, the variance of prior review ratings appeared to exert a positive impact on subsequent consumers' willingness to post online reviews. In other words, a dissentious rating environment could encourage subsequent consumers to post reviews in an online review community.

Third, positive disconfirmation (vs. positive confirmation) led to increased online review ratings. Individual consumers were apt to post higher review ratings when encountering positive disconfirmation compared to positive confirmation. This finding indicates that while perceived product quality and performance do influence a consumer's rating, disconfirmation between perceived quality and prior average review rating also matters. The motivation of concern for others increased significantly when consumers faced positive disconfirmation and thus encouraged increased online review ratings.

Fourth, the variance of prior review ratings attenuated the indirect effects of disconfirmation through concern for others. Specifically, the indirect effects of disconfirmation on consumers' willingness to post online reviews and review rating decisions were strong for prior review ratings with a small variance but weak for prior review ratings with a large variance.

Fifth, disconfirmation exerted significant impacts on consumers' online review content characteristics. Consumers facing disconfirmation tended to write longer and more sentimental reviews, including explanations why they deviated from past consumers. Moreover, other customers perceived disconfirmed reviews to be more useful. In addition to the direct effect of disconfirmation on review usefulness, disconfirmation could also increase review usefulness through changes in the review content. It was also found that the effects of negative disconfirmation were stronger than those of positive disconfirmation.

Sixth, this dissertation revealed that prior average review rating exerted a positive influence on subsequent review ratings for the same restaurant. By contrast, the above social influence process was moderated by the extremity of consumers' experience, the cognitive effort they devoted to writing a review, their online status, and the variance of prior review ratings. The influence of prior average review rating on subsequent ratings was stronger when the consumer had a moderate experience or invested less cognitive effort in writing an online review, whereas the influence was weaker when the consumer had an extreme experience or invested more effort in writing the review. Compared with non-elite reviewers, Yelp-classified elite reviewers were less susceptible to the social influence of prior average review ratings. Moreover, the influence of prior average review rating on subsequent ratings was stronger when the variance in prior review ratings was small and weaker when the variance was large.

5.2 Research Contributions and Implications

This dissertation contributes to the hospitality marketing literature and general marketing literature by offering new theoretical insights. The empirical findings unveil important managerial implications regarding online review management and digital marketing strategies for hospitality firms and online review communities.

First, the bidirectional nature of social influence on consumers' eWOM behavior related to hospitality products was tested. Online reviews, which influence others' purchase decisions, appear to be socially influenced by prior reviews posted by other consumers. This dissertation proposed a theoretical framework on how consumer online review behavior is socially influenced and tested it empirically using an experimental design and online secondary data from Yelp. Findings enrich the social influence literature and eWOM literature. From a managerial perspective, this dissertation raised questions regarding the reliability and objectivity of online reviews as accurate indicators of product quality; findings may help practitioners understand how review ratings and review content are socially influenced by prior reviews posted by other consumers for the same product. Given the importance of the accuracy of online reviews to the reputation of online review platforms, the results of this dissertation expand practical knowledge of online review management.

Second, the factors that potentially moderate the social influence of past consumers' online reviews were explored and empirically tested. This dissertation made an initial attempt to examine the social influence of prior reviews on subsequent review ratings for consumers with different product experiences (i.e., extreme vs. moderate), different statuses on Yelp (i.e., expert vs. non-expert), and for those investing different levels of cognitive effort in writing online reviews. The findings from this dissertation contribute to the literature on social influence and online review management, including by providing guidelines to mitigate the social influence of prior reviews and improve the accuracy of online product and service ratings. Such measures could help to improve the reputation of businesses and online review websites.

Third, although previous literature has explored the positive influence of disconfirmation on customer satisfaction, the relationship between disconfirmation and consumers' online review behavior has been largely overlooked. To extend this body of research, this dissertation empirically tested the disconfirmation effect on consumers' willingness to post online reviews, their online review content characteristics, and the asymmetrical effect of positive and negative disconfirmation. The findings contribute to the literature on the relationship between disconfirmation and consumers' post-purchase behavior in an online context. From a managerial perspective, the results provide meaningful implications for product marketers who may manipulate online reviews and ratings by posting fraudulent positive evaluations of their own products or negative reviews and ratings of their competitors' products.

This dissertation also offers worthwhile managerial implications for marketers and managers regarding online review manipulation and its consequences. Online review manipulation has expanded rapidly in the hospitality industry. To control their online reputation on third-party websites, many companies post fake reviews for their own products and those of their competitors (Gormley, 2013; Ho, Wu, & Tan, 2017). The findings of this dissertation indicate that inflated ratings can lead to negative disconfirmation, which increases consumers' willingness to post negative online reviews. Moreover, this dissertation indicates that negatively disconfirmed consumers tend to write longer reviews with stronger sentiments and greater cognitive effort in explaining the disconfirmation, potentially bringing worse damage to a company's brand image and long-term revenue. By contrast, when reading reviews of companies who received fabricated negative reviews, consumers are more likely to encounter positive disconfirmation, which will enhance consumers' willingness to post positive reviews and help compensate for abnormally depressed ratings in the long run. Essentially, online review manipulation does not work in the long term and may prove detrimental to product eWOM.

This dissertation also presents important practical implications for online review system managers. Offering true quality evaluations of products and services is a prime objective of online review platforms (Ma et al., 2013); therefore, platform managers should consider highlighting biased reviews or screening out review biases. The findings of this dissertation reveal a few measurable conditions under which consumers' review ratings tend to be socially influenced by prior reviews. By developing relevant algorithms, online review platforms can warn consumers if a review appears to exhibit strong social influence and instead showcase reviews that are less likely to be socially influenced. Consumers would benefit from these practices by making better-informed purchase decisions. In addition, online review platforms could also rate reviewers based on the factors identified in this dissertation and rank reviewers' reliability accordingly. A ranking system would potentially motivate reviewers to draft more objective, thorough reviews by investing additional cognitive effort in the task. This type of system would ultimately benefit online review platforms in the long term.

In general, all stakeholders have been inevitably affected by the social influence of consumers' online reviews in today's technology and business environment. First, for consumers, socially influenced online reviews may lead subsequent consumers to make inaccurate purchase decisions; at the same time, a consumer may be motivated to correct seemingly inaccurate online ratings posted by other consumers if there is a large deviance with his/her own consumption experience.

Second, for business owners, the social influence on consumers' online reviews may lead to the failure of the online review manipulation. Specifically, when businesses post deceptive positive reviews for their own products, negatively disconfirmed consumers may very possibly post review ratings that are lower than their actual experiences to compensate for manipulated review ratings (Ho, Wu, & Tan, 2017). Consumers also tend to write negative and longer reviews to express their disappointment, resulting in serious damage to hotels' and restaurants' revenue and brand image. On the other hand, for competitors who are plagued by fraudulent negative reviews, positively disconfirmed consumers tend to be more willing to post online reviews with ratings exceeding their own experiences. They also tend to write positive and longer reviews to express their surprise, which can correct for unfairly diminished review ratings in the long term.

Third, for online review websites, the social influence on consumers' online reviews may foster the sense that online review platforms may not be accurate and could even be misleading if online review manipulation occurs. If the ultimate goal of an online reputation system is to provide unbiased reflections of product quality, this research advocates and provides guidelines to mitigate the social influence of prior reviews and enhance the accuracy of online product/service ratings, which will eventually enhance the overall reputation of online review websites.

5.3 Research Limitations and Future Research Directions

This dissertation is subject to a few limitations, which can be addressed in future studies.

First, this work only tested the mediation effect of the eWOM motivation of concern for others on disconfirmation effects on consumers' online review behavior in terms of willingness to post online reviews and review rating decisions. It would be interesting to investigate the mediation effects of other eWOM motivations, including the need for uniqueness, helping a company, and self-enhancement.

Second, this dissertation did not consider the role of hotel or restaurant attributes in disconfirmation effects on consumers' online review behavior. Future research could evaluate the moderating effect of hotel/restaurant brands and price ranges. For example, the indirect effects of disconfirmation on consumers' willingness to post online reviews and review rating decisions out of concern for others may apply only to hotel/restaurant brands with poor reputations but not for those with high reputations. Consumers may be more likely to attribute disconfirmation to inaccurate review ratings on review platforms for brands with poor reputations (vs. high reputations) and express stronger concern for other consumers.

Third, although this dissertation considered many factors associated with social influence in the context of online reviews, some reviewer characteristics remain unaccounted for. Future studies should investigate the moderating role of reviewer characteristics, such as the reviewer's social network size and location within it, when evaluating the social influence process behind consumers' online review behavior.

Fourth, the dissertation sample came from Western culture, which may limit the generalizability of these findings. Previous literature has argued that compared with Western (or individualistic) cultures, individuals from Eastern (or collectivistic) cultures are more likely to conform. Therefore, subsequent research could involve a cross-cultural study of consumers' online review behavior.

Fifth, this dissertation assumed that consumers would post online reviews immediately after a consumption experience. In reality, however, time delays after a consumption experience in a restaurant or hotel is likely to affect the social influence process of consumer online review behavior. Memory strength theory (Hinrichs, 1970) posits that each item in memory has a degree of strength that may decline as time passes. Therefore, the time duration between consumption and posting a corresponding online review may influence how an experience is recalled, the extent of perceived disconfirmation, and the associated social influence process. In light of this phenomenon, future scholarship could examine the role of time delays in writing reviews if relevant data are available.

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